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# Study of the privacy paradox on health technology services cases of Coronalert and CovidsafeBE

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# Study of the privacy paradox on health technology services: cases of Coronalert and CovidsafeBE

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# Abstract

The adoption of government-issued health technology services is a timely topic because of the pandemic we face. Analyzing the decision-making of individuals in the context of technologies is of scientific interest because biases can be identified and interpreted. This research analyzes how the privacy paradox is at play in the context of government-issued health technology services. Quantitative research was conducted on Belgian citizens who own a smartphone to analyze the privacy paradox in the context of CovidsafeBE and Coronalert. The results of this research were used to analyze the different hypotheses formulated in our conceptual model. The findings are that the privacy paradox cannot fully be considered for Coronalert, but that some aspects of the paradox influence the adoption of CovidsafeBE.

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# Chapter 1: Introduction

## 1 Context

The twenty-first century has seen an impressive growth in the use of technologies. One of these technologies is social media, which is used by more than half of the world's population (Kemp, 2020). Technologies such as social media have allowed companies to apply data-centric product strategies (Saura et al., 2021). This strategy is possible because users generate a lot of data. Two ways are identifiable; users integrate personal data such as date of birth or home address; and users generate data with their activity on technologies such as social media. These types of data are part of "big data", i.e., large volume of data (Saura et al., 2021). It is composed of structured, semi-structured and/or unstructured types of data and the data generated by users is part of the unstructured data (Ghani et al., 2019).

Big data can be considered as a tool to keep track of the behavior of individuals to gain profit, or as S. Zuboff would say: "*big data is above all the foundational component in a deeply intentional and highly consequential new logic of accumulation that I call surveillance capitalism*" (Zuboff, 2015, p. 75). Surveillance capitalism occurs when data collected about users is used by companies for economic purposes, with little regard for the privacy of users (Saura et al., 2021). The main economic goal is targeted advertising, which is made possible by predicting users' behavior through the data collected about them.

User generated data worries users, because of what can be done with this data (Saura et al., 2021). The different risks linked with the use of data are: (1) data breaches, occurring when data is stolen from individuals or organizations; (2) the use of non-consented data, happening happens when organizations use users' data without them knowing; (3) the misuse of data by firms, happening when companies utilize users' data for non-initial purposes; and (4) the misuse of data by authorities, taking place when authorities use data to control or influence their citizens (She et al., 2020; Saura et al., 2020; Aridor et al., 2020; Curran & Smart, 2021; Meridith,2018).

A survey conducted by Deloitte shows that 58% of respondents want to reduce the amount of personal data available online but do not know how to do so (Data Privacy Awareness, 2020). This indicates that users have little trust in online platforms. This is confirmed by the winter

Eurobarometer of 2020 - 2021, 54% of respondents in the European Union do not trust the Internet and 68% of them do not trust social networks (*Standard Eurobarometer*, 2020, p.28,29). Similarly, many citizens are concerned about the misuse of their personal data. 41% of European citizens do not want to share their personal data with private companies. Additionally, 30% of the citizens are worried about advertisers, businesses, and foreign governments accessing their personal data (FRA, 2020). However, 75% of Europeans use the Internet daily or almost daily and 52% use social networks daily or almost daily (*Standard Eurobarometer*, 2020, p.130,132). Furthermore, more than half of the world's population uses social media as of July 2020. Only central Asia, South Africa, Central Africa, East Africa, and West Africa are below the bar of 50% of their population using social media (Kemp, 2020). The four most used social media applications are Facebook, YouTube, WhatsApp and Facebook messenger (Kemp, 2020). Yet Facebook, which owns WhatsApp and Messenger; and Google, which owns YouTube, are companies known to collect massive amounts of personal data on their users (Stucke, 2018). This points to a certain *privacy paradox* because even if users do not trust the Internet and social networks, it is evident they still use them. The privacy paradox is a phenomenon that describes the inconsistency between a user's attitude and their actual behavior. In other words, they will not protect their personal information online even though they are concerned about their privacy (Barth et de Jong, 2017).

Nonetheless, there are also positive aspects to data collection. It is beneficial in various fields such as healthcare or the public sector (Ghani et al., 2019). Healthcare is improved as big data is used to emit more accurate disease diagnostics or provide more personalized medicine; the public sector also benefits as needs are more easily identified and met, and new products and services can easily be issued through data analysis (Manyika et al., 2011). The spur in technology of the twenty-first century has enabled the public sector to implement e-government, which allows government services to modernize using available technologies. The interaction of e-government is done in different ways: from government to citizens, from government to employees, from government to business, from government to other governments and from citizens to governments. The rate of interaction between the different parties is increased, the information between them is also more transparent, and operating costs decrease (*Het Begrip E-Government*, 2021). Examples of applications of e-government in Belgium are eHealth, Coronalert, and Myminfin. The first is a website that citizens can access to view their medical records and health insurance (*EHealth*, n.d.); the second is an application

created for contact tracing in the context of the Covid-19 pandemic (*Coronalert*, n.d.); and the third is a website that citizens can use to view their tax calculations, real estate cadastral income or rental agreements, requesting an installment plan, or to pay off debts (*MyMinfin*, n.d.).

During the Covid-19 pandemic, several social distancing measures were installed worldwide to slow the spread of the disease. This virus emerged in late 2019 and in extreme cases can cause respiratory failure or septic shock among other things (WHO, 2020). Available technologies were very helpful during the Covid-19 pandemic, especially when social barriers had to be respected. Telecommuting was made possible so that people would not have to travel to their workplace, and families and friends were able to stay connected through various platforms such as social media. As a result, the use of social media increased during the pandemic (Drouin et al., 2020). In addition, governments around the world launched apps to raise awareness or to try to slow the spread of the pandemic (Utz et al., 2021). One example is contact tracing apps that alert people if they have been in contact with someone who has tested positive for Covid-19 (Fahey & Hino, 2020).

The contact tracing application raised many concerns among citizens about data privacy. They feared that the government could have direct access to their location, and some were worried that the government would use this information against them if they were not respecting social distancing (Rowe, 2020). A sort of privacy paradox can be identified in this case because citizens must make a decision between prioritizing data privacy or working together to fight the pandemic and thus give up some data privacy (Utz et al., 2021).

# 2 Research motivation

It is relevant to analyze the importance of users' data privacy in the current context. Indeed, even if they value their privacy, they are not able to protect it properly because of the way technology companies have designed their revenue stream to provide different services to users. These companies use the decision-making biases of individuals against them (Waldman, 2020). For example, they often make sure that users do not have all the information they need to make a rational decision, such as the monetary value of their private information (Wagner et al., 2021).

Some services that also collect data but are in the user's interest should bypass this data-driven strategy that is applied by profit-driven companies. This should be the case, for example, for government-delivered technology services (Fox, 2020).

Analyzing what influences users to not take rational decisions regarding government-issued health technology services is the motivation for this research. The importance lies in the context of the pandemic where health care is central, and the adoption of services could help citizens receive better care and the medical profession work more efficiently by focusing on patient treatment.

In doing so, we aspire to identify the different biases of the privacy paradox at play in the adoption of health technology services issued by the government to avoid possible misunderstandings. There are several possible reasons why this could happen, such as not having enough transparency regarding the use of data across the service's different platforms or not trusting the government. It is in the interest of the users that their decision to adopt the app is justified, but also in the interest of the government to incorporate what is important to the user so services can work at their full potential.

# 3 Academic motivation

The decision making of individuals has been studied for a long time. It analyzes how a person comes to a decision especially when that decision is not rational, that is to say, not only considering advantages and disadvantages (Simon, 1955). Several factors bias the decision such as loss aversion of a person or the influence of short-term benefits (Kahneman & Tversky, 1979; Laibson, 1997). The analysis of this phenomenon and its relationship with new forms of technology has been widely studied in recent years. More specifically, the privacy paradox, that occurs when users are inconsistent between their intended attitude and their behavior (Barth et de Jong, 2017).

Research into how users make decisions has already been conducted, but there is still much to discover as the technology grows exponentially. Now that governments are using it to communicate with their citizens, it is crucial to analyze how they can be influenced and why. One of the most important sectors, healthcare, has also chosen to take the path of phone apps to facilitate communication between medical stakeholders. The privacy paradox in the context

of government-provided health technologies has already been analyzed and the findings were that several elements influenced the acceptance and continued use of these technologies (Fox, 2020). However, it would be interesting if the same theories that are at play in the privacy paradox regarding social media are also applied in the case of health technology services.

The research conducted in this thesis is to analyze how users of government-provided health technologies are influenced by the biases identified in the case of social media use. The intent is to provide a better understanding of the choices a user makes regarding health technology services and whether those choices are influenced in the same way as social media services. The following question will therefore be analyzed during this thesis.

**How do the different theories that define the privacy paradox apply to the adoption of health technology services issued by the government?**

The research will be applied to the case study of two applications that were launched by the Belgian government during the Covid-19 pandemic, namely Coronalert and CovidsafeBE. The former is a contact tracing app, and the latter is an app that allows the user to have their Covid certificate (which can be obtained by being vaccinated, having recovered from Covid-19 or having a negative test for Covid-19) on their phone (Coronalert, n.d.; CovidSafeBE, n.d.). Analysis of how the privacy paradox applies to the adoption of these services will provide interesting new information because they are very recent, dating to 2020 and 2021, respectively. Moreover, analysis in light of a pandemic may provide a new way of looking at the privacy paradox in this context.

# 4 Approach

The purpose of this research is to analyze how the privacy paradox applies to the adoption of health technology services. The thesis is divided into two parts.

The first part is theoretical and consists of 3 chapters. The first chapter describes the use of data to be able to understand users' privacy concerns. Following this, the privacy paradox is introduced with the different theoretical concepts related to it. The last chapter is focused on the definition of the research problem and the creation of the conceptual model.

The second part of this thesis is an empirical study and consists in three chapters. The first chapter focuses on the introduction of the case studies and the methodology that is used to test the conceptual model. After that, the reliability and validity of the different constructs are tested before analyzing the results of the tests on the different hypotheses. Finally, the last part proposes a conclusion of this work and managerial recommendations based on the results of the analysis.

# Chapter 2: Literature review

## 1 Online data

This first chapter aims to present the data environment that consumers are confronted with, what is done with their data and what are the risks related to each step of the data processing. It will provide a better understanding of where users' privacy concerns lie and why they exist.

### 1.1 Data collection

#### 1.1.1 Definition

Data is collected by five main sources, (1) computer-mediated economic transactions; (2) data from sensors that can be found on objects, bodies, and places; (3) data from corporate and government databases; (4) data from private and public surveillance cameras; and (5) data that is collected on individuals and that is considered as "small" (Zuboff, 2015).

The "small" data is the data that is "left" by users online, which is also called user-generated data. It represents all the data users willingly and knowingly give such as birthdate, email, photos or likes, but it also contains data that users are not aware of such as the number of devices connected to their IP address or their type of personality (Saura et al., 2021). This data is collected by data-driven companies which allows them to predict the users' behavior and optimize the personalization of the service and/or product. In this way, the targeting of advertisement can be more precise.

#### 1.1.2 Risks, data breaches

One of the risks that comes along with any type of data collection are data breaches. A data breach is "*an occasion when private information can be seen by people who should not be able to see it*" (« DATA BREACH | meaning in the Cambridge English dictionary », n. d.). This means that if a data breach occurs there is a lack of privacy, and this may lead to drastic consequences such as a stolen identity (She et al.,2020). Data breaches happen daily, in 2019 there were 25 247 data breaches reported in the Netherlands alone, in Belgium this number was 912 (Johnson J., 2021). The risk of data breaches increases when data driven companies such as Facebook or Google sell the collected data to third-party firms (Lulandala, 2020).

According to Verizon (2020), the two sectors identified as having the most data breaches are the healthcare sector with 512 data breaches, or 12,96% of the total amount of data breaches in 2020, and the financial sector with 448 breaches, or 11,34% of the total amount. Furthermore,

according to previous research, the number of breaches has increased in the healthcare sector from 2010 to 2019, particularly due to hacking (Seh et al., 2020). This result is not surprising because these two sectors have the most sensitive information, healthcare displays the most personal information about individuals and financial information can lead to theft. Thus, the data monetization would be much higher in the healthcare sector or the financial sector due to the sensitivity of the data. For instance, the 2019 report of IBM security showed that every record that is breached costs $429 in 2019 in the healthcare sector and $210 in the financial sector, while the average cost per record across all industries was $150 in that year (*Cost of a Data Breach Report*, 2019).

Data breaches can occur in several ways. In the healthcare and financial sector, the main origins of the 512 and 448 data breaches are respectively: hacking, 145 and 193; malware, 33 and 32; social, 105 and 90; misuse, 73 and 35; error, 181 and 127; physical, 29 and (Verizon, 2020). Hacking is the action of using stolen login information, abusing weaknesses and attacking using backdoors and command & control functions; malware is the action of intentionally damaging or endangering a computer or stealing access to it; social actions refer, for example, to phishing, where someone is tricked into giving out information by mail or on the Internet so that the perpetrator can do things such as steal money from a bank account (« PHISHING| Meaning in the Cambridge English Dictionary, » n.d.); misuse is the action of using data in the wrong way; error action is, for example, the delivery of information to the wrong person; and physical action is a person stealing data in the form of paper or software (Verizon, 2020). The use of backdoors for hacking is the exploitation of vulnerabilities in computer systems in order to gain access to them without the need for the identification methods that are present in that system (« Backdoor definition », 2021).

The consequences of data breaches take many forms. For the user, there are privacy and security issues. For example, if enough information about the user is available, their identity can be stolen, and they can be robbed of their money. For businesses, this can lead to costs as mentioned above and a loss of trust from their customers (She et al.,2020). Previous research explains that data breaches have a negative impact on trust, one of the reasons being that users were reluctant to use Facebook ads shortly after a data breach was made public (Lulandala, 2020). Other assumptions that were made in this research were: "*perceived data breach has a negative impact on ad acceptance, data breach has positive impact on privacy concerns, data breach has a positive impact on emotional violation, data breach has a positive impact on ad avoidance, and data breach has a negative impact on ad engagement*." (Lulandala E., 2020,

p.59). Although these assumptions have not been confirmed by extensive research, they have been more or less confirmed by other sources such as the Penomen Institute, whose survey found that 65% of respondents had lost trust in the organization where a data breach had occurred (*The Impact of Data Breaches on Reputation and Share Value*, 2017) and by statistics from a survey conducted in the UK that showed that 45.4% of the 1269 respondents changed their willingness to share personal data online when they became victims of a data breach, 21.4% experienced no change (Johnson, 2021).

## 1.2 Data extraction

### 1.2.1 Definition

Data extraction can happen in two manners, with the user's consent (for example, the info users give to Facebook, such as a birthday date or a current address) or without the user's consent (for example, the info of the user's friends) (Zuboff, 2015). In the second case, the user may not even know that the company can have access to a certain type of information such as hobbies, personal appearance, or even daily whereabouts. To be able to collect this unconsented data a lot of data collecting companies apply a strategy of "*Incursion into legally and socially undefended territory until resistance is encountered*" (Zuboff, 2015, p.79), so companies have access to certain types of information without users being aware of it and by the time they do, a lot of non-consensual data has already been collected.

Users' consent can be obtained by data-driven companies by offering a service, with the information exchanged by consumers being considered as payment for the services offered by the company (Wagner et al., 2021).

### 1.2.2 Risk, negative perception of 'trade'

Above all, consumers need to be aware that the services they use online are not free and that they pay with their data. A 2020 study by Deloitte shows that 60% of consumers use WhatsApp, but only 40% of consumers who own a phone say their phone number is on the net (Lee & Calugar-Pop, 2020). This shows that a majority of consumers do not understand the extent to which their data is collected. Once consumers are aware of the trade they are effectuating with online services, consumers might be preoccupied by the perception they have about this trade. According to prior research, the exchange that occurs between consumers and providers can, in some cases, leave consumers feeling that they are "losing" the exchange if their information is overvalued relative to the service they receive in return (Wagner et al., 2021). Their study

confirmed five of their hypotheses concerning distributive equity i.e. (1) "*The higher users' perceived net values, the higher distributive equity perceptions of free data-driven service providers*.", this means that users weigh the amount of their form of payment (personal information) against what they get in return for the service; (2) "*The higher the perceived net value of free data-driven service providers, the lower distributive equity perceptions*", this means that if the provider's net value (benefits) is perceived to be too high from the users' point of view, they will consider that the exchange is not fair; (3) "*The relationship between provider's value of personal information and distributive equity is moderated by information sensitivity*", this means that users who consider their information sensitive will be more susceptible to the monetization of this data, which will influence their perception of fairness; (4) "*The higher users rate free data-driven service provider's distributive equity, the higher is their satisfaction with the provider*", this means that a user is more likely to be satisfied if the service is perceived as a fair exchange between data and service use; and (5) "*The higher users are satisfied with free data-driven providers, the higher is their continuance intention*", which means that satisfaction influences the intention of use of the user (Wagner et al., 2021, p.3 & 4). Their study was conducted on 200 Facebook users, arbitrarily they were shown a Facebook income from their personal data of 38 cents or 98 euros per year, after that a series of questions were asked. Thus, this study has shown that users are influenced by the monetization of personal data by providers. If this monetization is too high, the user will have a less fair perception of the personal information he/she gives compared to what he/she gains from using the service. In addition, the sensitivity of the information also influences users' perception of the fairness of the exchange. This sensitivity changes from one user to another, typically a person who has information that conforms to the norm will be less protective than someone that does not, e.g., an overweight person will be less willing to share information about their weight (Wagner et al., 2018). The importance of the valuation of personal data has become important because it is a form of payment that is often used in the technological industry, some users have become aware of this and require a fair remuneration in the form of monetization or services (Wagner et al., 2018).

### 1.2.3 Non consented data

Another risk that is possible when the extraction of data occurs is that unconsented data is taken from users. As the most used method to collect data is "*Incursion into legally and socially undefended territory until resistance is encountered*" (Zuboff, 2015, p.79) users are not always aware of what is collected about them. For example, Google employees admitted that location-

based privacy settings were potentially misleading and ambiguous during a consumer protection trial in Arizona (Center, 2020). The lawsuit was filed because Google collected and stored location data on mobile devices of users who had disabled location tracking, a violation of Arizona's consumer fraud act.

The types of non-consensual data that are collected are varied, for example: devices that are connected and nearby, which can be collected via WIFI access or location; health information through online health services or media applications; photos, which can be collected through users' social networks; and household income through content consumed online or items purchased (Saura et al., 2021).

## 1.3 Data analysis

### 1.3.1 Definition

To carry out data analysis, economy of scale is applied by companies such as GAFA (Google, Apple, Facebook and Amazon) so that the cost for analyzing is close to zero even though millions of virtual servers are required to increase the computing capabilities (Zuboff, 2015). In addition to the material, it is also necessary for data scientists to "*conduct predictive analysis, reality mining, patterns-of-life analysis, and so on*" (Zuboff, 2015, p.80). The different techniques related to social media big data analysis are (1) natural language processing, which analyses the human language used by users; (2) sentiment analysis, which involves identifying the sentiment of a specific text so that the analysis indicates whether the underlying sentiment is positive, negative or neutral; (3) Social Network Analysis (SNA), which analyses the different connections that exist between different users; and (4) news analysis, which is used to analyze the different news stories online (Ghani et al., 2019). These different techniques can also be used in areas other than social media, for example SNA is often used in the medical sector (Ghani et al., 2019).

### 1.3.2 Risks

#### *1.3.2.1 Misuse of analysis by firms*

One phenomenon that has demonstrated how data can be misused by businesses is the case of fintech applications in Kenya. Fintech is a technology that allows people to lend a small amount of money with a high interest rate (Kiruga, 2020). In order to use fintech applications, users must agree to terms and conditions that include sharing phone contacts, location, Facebook friends, etc., where the applications then use this information to publicly shame users

who do not pay back their debts. Shaming is done by sending messages to family, friends and colleagues informing them of the user's debt situation (Roussi, 2020). To address the practice of some fintech applications, the Kenyan parliament is in the process of issuing a new law so that the interest rate can only be changed with the approval of the central bank (Kiruga, 2020).

To protect users' personal information authorities introduced the General Data Protection Regulation (GDPR), however, previous research studying the effects of this legislation concluded that they were not all beneficial (Aridor et al., 2020). In their research they found that the persistence to track customers via cookies increased post-GDPR. To explain this they analyzed a hypothesis, "privacy means substitution hypothesis" (Aridor et al., 2020, p.20), which means that users who were already privacy protection driven were now able to apply the opt-out of data collection GDPR provides. This implies that there is near to no data collected about the user. On the other hand, the previous cookie-blocking aids in the browser aren't used anymore. This tool created new cookies/ identifiers every time the customer went on the specific website, causing an interference the behavior predicting algorithms because two or more profiles were in fact the same person. But now, with the new regulation, there is no data stored about this particular customer, allowing the algorithm to be more accurate with behavior prediction because it considers one profile for each visitor. There are several economic consequences with this hypothesis. Firstly, the people who were already concerned about their privacy and now use the opt-out option must analyze the profit they have between pre- and post-GDPR. Secondly, the users who do not use the opt-out and thus do not protect their privacy as well as the previously mentioned customers may be disadvantaged by the introduction of GDPR. This is due to the more precise behavior predictions, as previously mentioned. Ultimately, this would mean that advertisements would be more adapted to each visitor that is willing to share their data, increasing the price of placing an advertisement. To support this hypothesis, the paper provides evidence about the number of cookies that are used to track one user. In the post-GDPR situation this number decreased significantly, which is in line with the number of cookies that were created with browser-based privacy tools. The research does not identify a proven effect on users who are not using the opt-out options. It could be beneficial if companies use the data to adapt advertisements and services to their needs. This could lead to pricing users differently according to their online behavior. Nevertheless, privacy-concerned users have a positive outcome of the GDPR because their digital footprints are erased and, in this way, they have more online privacy (Aridor et al., 2020). Thus, this analyzed online

behavior is used by companies to differentiate the product they offer according to specific user profiles and this identification could be even more precise due to the GDPR.

#### *1.3.2.2 Misuse of analysis by authorities*

An example that can be considered as data misuse by authorities is the social credit system used in China. This system allows "points" to be awarded to citizens, the higher the number of points, the better it is for the citizen. The system is used to allocate a loan, rent an apartment, etc. However, there is no clear indication on how the points are awarded, as the standards are defined by business and private interest, but in general, if a citizen commits a crime or does not follow the standards, their points decrease (Curran & Smart, 2021). However, it seems that if a person buys a video game or if his friends' activities are perceived as bad, this also negatively influences the score of this person (Walraven, 2018; Curran & Smart, 2021). Thus, an individual with a low social credit score will have difficulties to raise it because the system is not transparent. Nonetheless, the system does reduce, or even remove, crime, as it lowers the score drastically. But this system has no place for outcasts, because if a person is not part of the system, he or she cannot do anything. Moreover, people with a low score will have more difficulties to access certain types of resources or social legitimacy, while people with high scores will find it easier to continue to prosper in society. Thus, this system widens the gap between the rich and the poor. Furthermore, this score could influence dating and marriages if it is made available to the public. In addition, this system disadvantages minorities such as LGBTQ people or people who are critical of the government because of the entrenched traditional values (Curran & Smart, 2021).

Another example is the use of data analysis to better target citizens in the case of elections. One instance where this has occurred was the Cambridge Analytica scandal, uncovered in 2018. The firm was working in the field of political consulting and was able to collect data through a personality test application created by a researcher conducting a study for academic purposes (Meridith, 2018). This data was obtained through the app which collected data on the respondent as well as all their Facebook friends, who had not given their consent. Through this technique, data from more than 87 million Facebook profiles were collected. Cambridge Analytica had been accused of influencing the 2016 US presidential elections, using the data collected they identified undecided people and targeted them with specific advertisements for Ted Cruz's campaign and later for Donald Trump's (Meridith, 2018). Facebook was fined because they were accused of not protecting their users' data sufficiently (Wong, 2019) and

Cambridge Analytica went bankrupt in May of 2018 (Staff, 2018). The situation raised awareness about data privacy and some users even wanted to delete Facebook (Chen, 2018). In the end, the Cambridge Analytica scandal was reported as one of the largest data breaches of a technology company (Cadwalladr et al., 2018).

## 1.4 Solutions to strengthen privacy

In order to strengthen online privacy, users must first be aware of the dangers of using online services. Individuals must therefore understand that these services are not free and that they pay with their data (Wagner et al., 2021). Governments could play a role in educating their citizens so that they can protect their own online privacy (Walraven, 2018). Once users are aware of the exchange they are engaging in, there are several steps they can take to enhance their privacy (Walraven, 2018). For example, the user can take advantage of the regulations stemming from the GDPR, which was introduced in 2018 to protect data subjects, by managing the various cookies on websites and ensuring that the non-essential ones are rejected. Another possibility is to use other search engines that collect less data than Google, such as Ecosia or stratpage.com. In addition, users should use complicated and long passwords to avoid being hacked. This list of steps is not exhaustive.

However, the GDPR, had some unintended consequences regarding competitiveness in some sectors. In the web technology provider sector, there has been an increase in market concentration which has mainly benefited Facebook and Google, this increase was due to websites deciding to work with larger providers because they trusted them more to deliver a better-quality product and to better implement GDPR (Johnson et al., 2020). Another sector that has been negatively impacted is the ad tech sector, for several reasons; (1) Google benefits from its notoriety in user consent; (2) Google benefits from its internal “free data flow” policy which gives it an advantage over its competitors as it has a wide range of services to offer ; (3) Google benefits from the human and financial resources it has to comply with the GDPR, which is not the case for smaller companies; and (4) Google has been able to take advantage of the “one-stop shop” which gives it the possibility to deal with complaints with a single Data Protection Officer, DPO, in its main establishment in Europe which is located in Ireland, which is known to apply the GDPR more flexibly than some DPOs in other countries (Gerandin et al. , 2020). Furthermore, the benefits the GDPR brought to data subjects are questionable (Aridor et al., 2020), (c.f. 1.4.2.1). The three papers therefore propose to adapt the GDPR to take into account the competitiveness of the different markets and to further protect users.

The Commission Nationale de l'Informatique et des Libertés, CNIL, which regulates and monitors compliance with the various data protection laws in France (*CNIL* |, n.d.), has introduced a new regulation that goes beyond the GDPR. The new regulation had to be adapted by the end of March 2021 and ensures that rejecting cookies is as easy as accepting them on websites (Reisacher, 2021). As a result of this regulation, some websites offered users two options: accept cookies and continue browsing as normal or reject cookies but pay to browse the site. Thus, the solution to avoid advertising cookies is to pay. This solution is considered legal by the CNIL as long as the amount of money requested is fair (Reisacher, 2021).

Furthermore, several projects have been launched to enable more privacy in the future. For example, DECODE, a project funded by the European Commission, aims to find a way to give back control of personal data to those who own it in the first place (*What Is DECODE*, 2017). The project was based on data commons, which is a data set that would be of public property; decentralized servers, so that the data cannot be easily hacked or manipulated; and blockchain with attribute-based cryptography techniques, so that intermediaries are no longer needed (Walraven, 2018). Blockchain is a system that allows a record of every purchase and sale of a cryptocurrency (such as Bitcoin) in the form of blocks, with each occurrence representing one block ("BLOCKCHAIN| Meaning in the Cambridge English Dictionary," n.d.). Cryptography is the practice of encrypting information using certain codes ("CRYPTOGRAPHY| Meaning in the Cambridge English Dictionary," n.d.). The data available in the datasets would be voluntarily given by the users. Different pilots were put into place in Amsterdam and Barcelona, they offered alternative forms of online social networking and privacy-friendly services. The project that ran from 2017 to 2019 allowed them to develop a list of recommendations and advice on three levels, namely city, national and European so that the project could be applied on a larger scale (Bass & Old, 2020). Another interesting project is the Indienet created by Aral Balkan and Laura Kalbag (Fish, 2018), which was a private initiative, they wanted to create a web that was not influenced by surveillance capitalism. Surveillance capitalism was defined by Zuboff S as "a new form of information capitalism that aims to predict and modify human behavior as a means to produce revenue and market control" (Zuboff, 2015, p.75). Here again the project is based on decentralized networks, and the social networks would become a public service (Walraven, 2018).

# 2 Theoretical concepts

The previous section, online data, provided an understanding of why and how data is used. It also explained the risks that are associated with the collection, extraction, and analysis of data. This next section will explore the privacy paradox that occurs when users engage with online services in exchange for their data.

## 2.1 Definitions

The privacy paradox (cf 1.1) observed in the behavior of users has been the subject of several studies. According to Berth et de Jong the decision making of the users can be divided into two categories: “risk-benefit calculation” and “prevalent benefits and little to no risk assessment”, these categories are also divided in sub-categories (2017, p. 1040). Table 1 provides an overview of the different theories related to the different categories and subcategories established by Berth et de Jong (2017, p. 1041, 1042). Each category and subcategory will be explained based on a selected theory and the following sub section will contain a recent article that applies the theory to the user context of data-driven businesses.

## 2.2 Privacy concerns: theoretical foundations

The role of rationality, Rational choice theory of human behavior

Previous research tends to rely on rational choice behavior (Wagner et al., 2021), where there is an exchange of data and services online. Users should want the exchange to be positive for them, in other words, that the benefit from the service they receive is sufficient relative to the risk they take in giving out personal information. However, theories of behavioral economics (cf. table 1) show that users' decisions are not always rational and are biased by several factors.

(Immediate) role of gratification, Hyperbolic discounting theory

Previous essays have confirmed that hyperbolic discounting theory is one of the biases associated with risk-benefit calculations and is applicable in the context of user privacy (Waldman, 2020). Users will be more likely to disregard their online privacy in order to access online services, such as contact with online friends and the convenience of easy access to online searches, than to protect their data, even if they are aware of the risks involved. Thus, the immediate benefits are more important to users than the risk of losing their privacy in the long run, so users share their information now.

| Main category | Sub-cluster | | Theory | Explanation |
|---|---|---|---|---|
| Risk-benefit calculation | | | | This category of the decision-making process reflects the comparison of perceived benefits and risks when a consumer uses an application or website. |
| | Guided by rationality | | Rational choice theory of human behavior (Simon, 1955) | When a decision is guided by rationality, the user will weigh the benefits against the risks and make a decision that will be most beneficial to themselves. Thus, the utility will be evaluated by taking into account the risk that the individual is about to take. |
| | Biased risk assessment within the risk-benefit calculation | | | The calculation of risks and benefits can be confounded by a variety of factors, prompting users to base their decision on, for example, experience or trust in the ethics of companies using data. |
| | | (Immediate) gratifications | Hyperbolic discounting theory (Laibson, 1997) | Hyperbolic discounting theory states that individuals will perceive positive short-term effects as more valuable than positive long-term effects, even if the long-term effect is more beneficial than the short-term one. There is thus an inconsistency in the choices that are made when time is considered because the individual in the future will regret what he did in the past if the benefit would have been greater. |
| | | Under-/overestimation of risks and benefits | Theory of under insurance (Kunreuther, 1984) | According to the theory of underinsurance, which was defined by analyzing individuals' decisions to insure themselves if they live in disaster-prone areas, several aspects influence individuals when estimating risks and/or benefits. Individuals may make an incorrect judgment about a situation if they are influenced by experience, if they consider what their friends are doing, if they lack knowledge about how to protect themselves, if they do not understand the likelihood of an event occurring, or if they want to avoid admitting the risk situation because they do not want to live in fear. |
| | | Heuristics | Cognitive heuristics (Tversky et Kahneman, 1975) | Cognitive heuristics are mental shortcuts that allow individuals to make decisions more quickly. Tversky and Kahneman describe three of them, “representativeness” which helps one make a decision by comparing the event or object that an individual is to evaluate to what he/she already knows, “availability” which helps one make a decision based on examples that come easily to mind about the subject of the decision, and “adjustment and anchoring” which allows one to make a decision based on a certain initial idea and adjust from there. However, all three of these heuristics can be biased, for example, when the individual is influenced by stereotypes, when examples that come to mind are considered more important than information that does not come directly to mind, or when the initial anchor is the wrong value. |

| | | | | |
|---|---|---|---|---|
| | | Difference btw the judgements of risks and benefits | Prospect theory (Kahneman & Tversky, 1979) | According to Kahnemand and Tversky's prospect theory, decisions are made in two phases: editing first, and then evaluating. During the editing phase, people set a benchmark to determine what will be considered losses (below the line) and gains (above the line). During the evaluating phase, people will value the utility of the outcomes of the decisions they have to make based on the baseline established in the previous phase. The theory also states that an individual will react more harshly if it's a risk than if it's a gain. Thus, the way the decision is presented will influence the decision an individual makes. |
| | | Habit | Theory of ritualized media use (Rubin, 1984) | This theory, based on a study of television viewing, states that media has become part of everyday life. Different motivations of users to watch television were analyzed and all correlated with habit but viewing for information. |
| Little to no risk assessment | | | | In some cases, individuals do not possess or perceive knowledge of the risks associated with a decision. In this case, the individual will make the decision with little or no consideration of the risks and will base decisions only on the perceived benefits. |
| | Value of desired goal outweighs risk assessment | | Conformity and peer group pressure (Crutchfield, 1955) | Peer group pressure ensures that the individual allows himself to be influenced by the actions of those within the group in order to feel part of the group. |
| | Privacy valuation failed | | Public value theory (Meynhardt, 2009) | Public value theory shows that the individual is central and analyses the impact of individuals' subjective evaluations and perceptions on social relations. In this way, an organization can contribute to the well-being of a society. Thus, this theory can help in understanding the evolution of societal obligations and the making of values in societies that want to coordinate, legitimize, and give meaning to themselves. |
| | Knowledge deficiency due to incomplete information | | Theory of incomplete information (Harsanyi, 1967) | The theory of incomplete information shows that an individual is not always aware of the values and rules of another or is unaware of some important features of the environment in which he finds himself. |

*Table 1: Theories of decision making*

Under-/ overestimation of risks and benefits, Theory of under insurance

Users often misjudge the benefits and risks, i.e., they do not apply privacy safeguards for low probability but high impact risks, such as the one described in 1.5, § 1. This could be due to users not fully understanding how their data is collected and/ or not informing themselves by not reading the terms and conditions when using a service from a data-driven company (Lee & Calugar-Pop, 2020). Alongside this, the effect of experience is observable as previous research has shown that willingness to share information changes when a data breach has occurred (Johnson, 2021). This shows that the underinsurance theory is effective in the case of user data protection, lack of knowledge and reluctance to inquire will have a negative impact on a user's data privacy. A change will be observable when the damage has already been done, as was the case in Kunreuther's research when individuals took out insurance after two years of flood damage (1984).

Difference between the judgements of risks and benefits, Prospect theory

Regarding the privacy concern when a user is confronted with data collection, prospect theory has been proven to be accurate in previous research (Liao et al., 2020). The willingness to share data in order to receive non-monetary services in exchange will vary depending on the reference point, when it is high users are more lax in privacy; loss aversion; and risk parameter of the users. For example, users with a higher reference point, a high level of loss aversion and a low level of risk parameter will be more willing to participate in data collection. Because of the high reference point, users will not easily feel the loss of privacy, so the cost of participation will decrease, but because their loss aversion is also high, they will be sensitive to the loss of potential services if they do not participate. In contrast, users with a higher reference point, low loss aversion, and a large risk parameter will be less likely to trade their data for services. This is because they perceive the decrease in privacy due to the higher benchmark as less important than the gain in privacy if they do not participate.

The role of Habits, Theory of ritualized media use

According to the European barometer, 75% of respondents use internet daily and 52% use social media daily (*Standard Eurobarometer*, 2020, p.130-133). These percentages indicate that the use of the services offered by data-driven companies have often turned into a habit. The definition of a habit is "*something that you do often and regularly, sometimes without knowing that you are doing it*" ("HABIT| Meaning in the Cambridge English Dictionary," n.d.).

The impact of Heuristics, Cognitive heuristics

Previous research has shown that heuristics have an influence on how users protect their personal information online and this helps to explain the privacy paradox (users that give more information than they say they would). A recent paper studied several privacy heuristics and identified 12 of them, this list is not exhaustive (Sundar et al., 2020). (1) Authority refers to the influence of the name, brand, or organization of the website a user visits; (2) bandwagon is the influence of other users of the site/application who have already shared personal information; (3) reciprocity represents the influence of another person who has already shared personal information with the user; (4) sense-of-community denotes the influence of the community in relation to sharing data within the community; (5) community-building represents the influence of the desire to build a community by sharing information; (6) self-presentation signifies the influence of the user's desire to represent themselves by sharing information; (7) control means the influence of the control 'offered' by a site over users' private information; (8) instant gratification represents the influence of the speed with which a service is offered when a user shares information; (9) transparency is the influence of the transparency that a website gives to its users; (10) machine represents the influence of the thought that machines protect personal information; (11) publicness represents the influence of the public treatment of information; and (12) mobility represents the influence of the users' belief that mobile devices do not process information securely. The hypotheses made in the research, "*stronger belief in authority, bandwagon, reciprocity, sense-of-community, community- building, presentation, control, instant gratification, transparency, and machine heuristics will be associated with greater disclosure intentions in scenarios featuring cues related to those heuristics*." and "*Stronger belief in the (g) publicness and (h) mobility heuristics will be associated with negative disclosure intentions in scenarios featuring cues related to those heuristics.*" (Sundar et al., 2020, p.3, 4) were confirmed. Thus, mental short cuts that are used to make decisions influence the decision-making in the context of online privacy protection.

Value of desired goal outweighs risk assessment, Conformity and peer group pressure

Previous research has shown that users are influenced by the members of a group they want to be part of (Sundar et al., 2020). For the privacy protection aspect, this translates into a greater willingness of users to share information in order to be part of a group. Users will therefore be more likely to only consider the benefits of sharing data to access online platforms.

Privacy valuation failed, Public value theory

Data privacy needs to be valued if it is to be seen as a public value, this has not always been the case, but people are now increasingly aware of it. A 2020 survey by KPMG shows that 87% of the 1,000 respondents consider data privacy to be a human right and that users want organizations to commit to better protection, management, and ethical use of personal data. (*The New Imperative for Corporate Data Responsibility*, 2020).

Knowledge deficiency due to incomplete information, Theory of incomplete information

Users do not have full information about the dangers of privacy disclosure, this was shown in previous research (Lulandala, 2020). For example, companies may choose to hide the security breaches it has experienced so that they can maintain the trust users have in them. In this way, the user does not have complete information to make the right decision (Lulandala, 2020). This shows that incomplete information has an impact on the choice of a user.

# 3 Conceptual model

In the previous section, different theories on decision making were explained and shown in existing research to be applicable to the topic of privacy. They were mainly analyzed in the context of private data companies that offer services such as social media or online shopping. However, with the emergence of technology over the years, governments are also using IT to provide certain services. Examples of government applications and websites in Belgium include the eHealth (*EHealth*, n.d.) website which allows an individual to access their medical records online; the Coronalert (*Coronalert*, n.d.) application which tracks the spread of the coronavirus; and Myminfin (*MyMinfin*, n.d.) which allows an individual to have an overview of their house, property and information on payments and reimbursements and which helps them to fill in their tax return. The different theories identified above are interesting when applied to government applications or websites. The cognitive heuristic of authority that influences users through a name, brand, or organization (Sundar et al., 2020) comes into play in this case, as these platforms are issued by the government. In this way, we can analyze the privacy paradox in a different manner.

The analysis of healthcare-related websites or applications is also an interesting perspective to take because, as we saw earlier (c.f. 1.3.2), this information is considered sensitive, and users are therefore more likely to protect it. In addition, the health theme is very topical due to the global pandemic we are facing.

Previous research has already analyzed the privacy paradox of government-provided healthcare technologies by testing different hypotheses such as "*Perceived benefits will positively influence acceptance of electronic health record systems", "health information privacy concerns will negatively influence acceptance of electronic health record systems", "Perceived benefits will positively influence intention to adopt mobile-health technologies" and "health information privacy concerns will negatively influence to adopt m-health technologies*" (Fox, 2020, p. 1017). The different biases that were significantly influencing the acceptance or continuance of use of the different governmental IT health services were "*lack of privacy knowledge; underestimation of privacy risks; belief negative outcomes are unlikely; overestimating benefits; belief benefits are guaranteed; excessive data request; awareness of privacy risks; privacy breach; realization of benefits; and sustained relevance of benefits*" (Fox, 2020, p. 1025). However, this study has some limitations, including the fact that it does not analyze the actual adoption and use of the different services as well as the fact that it analyzes two different countries (Ireland and the United States) with different electronic health record systems. Therefore, the following question is interesting to analyze:

**How do the different theories that explain the privacy paradox apply to the actual adoption of health technology services issued by the government?**

We chose to analyze the risk-benefit calculation that a user makes when using a new website or downloading a new government-issued application because health data is sensitive, and users are more likely to already know the risks associated to the sharing of their data. Several theories were chosen for this analysis: rational choice theory of human behavior, cognitive heuristics, theory of under insurance, hyperbolic discounting theory, and theory of ritualized media use. The prospect theory will not be applied in this research because of its complexity. The different hypotheses that are analyzed in this study are explained in the following section.

## 3.1 Hypotheses

The various hypotheses that have already been proven in the context of data privacy (c.f. 2.2) will now be placed in the context of data privacy in a healthcare government environment. To this extent, each theory will be used to make hypotheses in the case of downloading or using a government application or website.

### 3.1.1 Rational choice theory of human behavior

As explained earlier, users must make a decision whether to download and use an online service or not (Berth and de Jong, 2017). Regarding the research question mentioned in the previous section, users have to decide on the adoption of government health technology services. The decision that users make is based, like any decision that must be made, on weighing up the risks and benefits (Simon, 1955). Previous research has confirmed the impact of perceived benefits on acceptance of electronic health record system (Sundar et al., 2020). In addition, the benefits identified will encourage someone to take the plunge (Simon, 1995), in our case the plunge is the adoption of governmental health technology services. Therefore, a pertinent hypothesis is the following.

**H1:** Perceived benefits will positively influence the adoption of governmental health technology services.

Furthermore, the various risks identified regarding data privacy will lead an individual to avoid options that carry many risks (Simon, 1995). The effect of privacy concerns on the acceptance of electronic health record systems has already been demonstrated (Fox., 2020), but as explained earlier the actual adoption needs to be analyzed. Therefore, the following hypothesis is made.

**H2:** Perceived risks regarding data privacy will negatively influence the adoption of governmental health technology services.

### 3.1.2 Theory of under insurance

This theory can be used to understand why individuals don't take actions to protect themselves regarding eventual risks. Two of the reasons being not having enough knowledge about the risks and not having experienced the possible risks (Kunreuther, 1984).

Knowledge

Not having enough knowledge about how data is collected and how it is used makes users less aware of the risks and therefore they do not apply privacy-protective behavior (Lee & Calugar-Pop, 2020). It would be logical that the reverse is true, i.e. the more knowledge a user has about data processing, the more protective that person will be of their personal data. Furthermore, if users do not have sufficient knowledge about the use of online data, they will be more likely to consider only the perceived benefits (Lee & Calugar-Pop, 2020). To consider these interpretations to our case is interesting, so we consider the following hypotheses.

**H3a:** Knowledge about data treatment has a positive influence on the perceived risks of using government health technology services.

**H4a:** Knowledge about data treatment has a negative influence on the perceived benefits of using government health technology services.

Experience

Studies have shown that users who have experienced a data breach have more privacy concerns (Lulandala, 2020). They are also likely to engage in data protection behavior (Johnson, 2021). Therefore, they are more likely to concentrate on the possible risks than the benefits of using the different platforms (Berth and de Jong, 2017). Analyzing this phenomenon in the case of government-delivered health technology services is relevant, as it will allow us to see whether data breaches in different platforms influence healthcare platforms.

**H3b** Data breach experience has a positive influence on the perceived risks of using government health technology services.

**H4b** Data breach experience has a negative influence on the perceived benefits of using government health technology services.

### 3.1.3 Cognitive heuristics

Testing all twelve heuristics identified in the research of Sundar et al. (2020) will not be possible since there are four other theories to test, so there must be a selection based on the assumption of what will be observable in the context we chose. The heuristics that are not used are reciprocity, sense of community, community-building and self-presentation because they cannot be adequately analyzed as other users are unable to check whether an individual is sharing personal information as data on government platforms is not made public; instant gratification will not be analyzed as a heuristic because hyperbolic discounting theory is more appropriate to do so; machine, mobility and publicness are not used because the focus of this thesis lies elsewhere. The different heuristics that are used to analyze the adoption of governmental issued platforms for healthcare are authority; bandwagon; control; and transparency.

Trust

The influence of government authority is supposed to inspire confidence in users as platforms are issued to make their lives easier, to help them get the right information and, in some cases, protect them. For example, the eHealth platform in Belgium was designed to provide electronic data and services to and from health stakeholders, while protecting the data

privacy of the patient and the caregiver so that medical confidentiality is respected (*MHealthBELGIUM*, n.d.). Therefore, the authority heuristic that inspires trust should strengthen perceived benefits and weaken the perceived risks of using government health technology services. However, the Winter Eurobarometer shows that in Belgium, 59% of respondents tend not to trust the government (*Standard Eurobarometer*, 2020). Thus, if the majority of citizens do not trust the government in Belgium, it is interesting to analyze the influence of the lack of trust in the issuing authority of the application or website. We will call this variable trust because it reflects the trust citizens have in their government. The hypotheses will be the following:

**H3c** The lack of trust in the government positively influences the perceived risks of using government health technology services.

**H4c** The lack of trust in the government negatively influences the perceived benefits of using government health technology services.

Bandwagon

The bandwagon heuristic shows the influence that other people can have on a person's decision (Sundar et al., 2020). Previous research has shown that the bandwagon effect encourages users to use Facebook and therefore to ignore the risks associated with using these services (Fu et al., 2012). This effect that has been established in the case of social media is interesting to test in our case. It is therefore relevant to consider the following hypotheses.

**H1a** The negative influence of perceived risks is weaker on the adoption of governmental health technology services when users are influenced by other active users.

Control

Users can be influenced by the degree of control they have over their data to download or use a certain application or website, the more control they have, the safer they feel to share their private information (Sunder et al., 2020). To analyze whether this is also valid for our case, the following hypothesis is made.

**H1b** The negative influence of perceived risks is weaker on the adoption of governmental health technology services when users are in control over the data they share.

Transparency

The various government platforms such as eHealth or Myminfin contain a lot of information about the cookies they use on their website and the data they collect and why (*EHealth*, n.d.; *MyMinfin*, n.d.). This suggests that transparency is present on these sites. The effect of transparency on willingness to share data has been confirmed in previous research, users feel

safer to share their information if the privacy policy is transparent (Sundar et al., 2020), however this research did not consider the intentions of a specific organization such as a government. It is therefore interesting to see whether users' perceptions of the risks of adopting government health technologies will be influenced by the transparency of a governmental issued platform. Therefore, the following hypothesis is pertinent.

**H1c** The negative influence of perceived risks is weaker on the adoption of governmental health technology services when the government's privacy policy is more transparent.

### 3.1.4 Theory of ritualized media use

The theory of ritualized media use explains that there are several habit-related reasons why a user uses media. This habit may influence users to lower their guard regarding data privacy in order to continue to use the media. (Stockdale & Coyne, 2020).

Habit

As shown earlier, the use of the internet and social media has become a habit. The influence of this habit can make sure that the perceived benefits become more important than the perceived risks in case of social media use, so the user will not engage in privacy protecting behavior (Debatin et al., 2009). For this research, it is therefore interesting to analyze how the use of the internet and apps as a habit can affect the perceived risks and benefits of the adoption of governmental health technology services. In this way, we can see whether the user's perceived benefits and risks is changed as a result of this habit. The hypotheses to be tested are the following.

**H5e** The perception of applications as a habit negatively influences the perceived risks of using government health technology services.

**H6e** The perception of applications as a habit positively influences the perceived benefits of using government health technology services.

### 3.1.5 Hyperbolic discounting theory

This theory allows us to analyze how immediate gratifications influence a user's choice regarding the downloading or using of governmental issued platforms. So, the understanding of the use and the perception of the immediate benefits of this same application will influence a user.

Immediate benefits

The link between perceived benefits and immediate gratification in the case of social media has already been demonstrated: users tend to "give up" their privacy if they have easy access to

online services, which also reflects less consideration of possible risks (Waldman, 2020). It is then interesting to see if this applies to the adoption of government-issued platforms, as some platforms do not have immediate benefits. For example, the Covid-19 tracking application only has long-term results in terms of the spread of the virus (Rowe, 2020), but the eHealth platform provides immediate access to medical records (*MHealthBELGIUM*, n.d.). Thus, the following hypotheses are relevant for analysis.

**H5d** Immediate benefits negatively influence the perceived risks of using government health technology services.

**H6d** Immediate benefits positively influence the perceived benefits of using government health technology services.

## 3.2 Conceptual framework

As a result of the hypotheses made in the previous section, the conceptual model that will be discussed in this paper is presented in Figure 1. This model will be tested by conducting a study that will be introduced in the next chapter of this thesis.

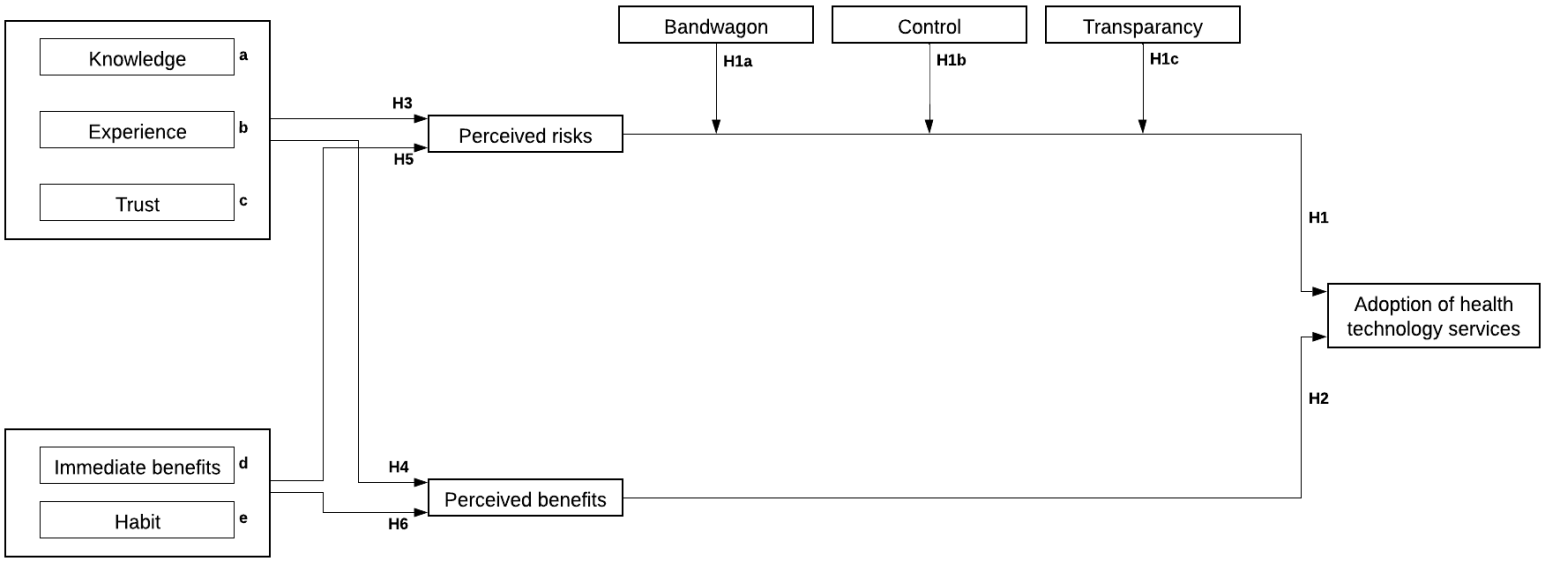


*Figure 1: Conceptual model*

# Chapter 3: Research Design

In the previous chapter, the conceptual model with the different assumptions that derived from it was presented. In this chapter this conceptual model will be tested by applying it to two cases studies. The case studies are the adoption of the Covid-19 tracing application and the Covid-19 certificate application.

## 1 Case study

In order to apply the conceptual model, we first need to understand the two applications mentioned above, why they were created, how they work and what concerns users may have about them. To begin with we present the tracking application that was introduced in several countries to monitor the spread of the pandemic and explain why some citizens were not very receptive to this new application. Then we will present the new application that was introduced in Belgium, among others, to identify whether a person has a Covid-19 certificate. In addition, we will draw up a comparison table between the two applications to analyze the differences and similarities.

### 1.1 Covid-19 applications

Since the outbreak of SARS-CoV-2, which is a disease causing "severe acute respiratory syndromes" in late 2019, several technology services have been launched, among others, to raise awareness of this highly contagious disease and track its spread (Utz et al., 2021, p.1). These technologies have often taken the form of apps and have been launched by private and public initiatives (Utz et al., 2021).

#### 1.1.1 Covid-19 tracing application

Intended use

In the opinion paper by R.A.Fahey and A. Hino published in 2020, authors explain the two different ways in which nations have applied the tracing application for Covid-19. There is the "data-first" view, where data is central and the more data that is assembled the better. The second is the "privacy-first", which ensures that when data is collected it remains anonymous and cannot be associated with any individual. Both approaches start in the same way, i.e. if a person tests positive and this is reported on the application, the people who have been in contact with that person will be alerted. However, the data-driven approach allows the authorities to know the identity of the people who have been in contact with someone who was tested positive

and to contact them. Whereas the privacy-based approach simply sends a notification to the phone of these people. The data-driven approach also allows authorities to identify clusters, which is not the case with the privacy-based approach. The data-driven approach has been used in, among others, South Korea, Singapore, the UK, France, Taiwan, China, Iran and Qatar. The privacy approach has been adopted, among other, in Germany, Italy, Japan and many US states. Apple and Google have created a framework for privacy-based approaches with a decentralized technology that have been adopted in several countries because they are technologically advanced, avoid problems such as excessive battery consumption and are trusted by a large number of citizens (Fahey & Hino). The decentralized technology allows to protect personal data, if the data is centralized it allows for data analysis (Meyer, 2021).

In Belgium, they adopted a privacy-first approach by using a decentralized privacy-preserving proximity tracing, DP-3T, structure. For the "Coronalert" application, the federal authority authorized Sciensano to create a database V that monitors the application's operations. Database I and II, which are also monitored by Sciensano, and which exist for treatments and scientific research in the health field, are separated from V so that no identification is possible. The application generates secret keys stored on users' phones that generate ephemeral identifiers that are renewed every 10 to 20 minutes. The technique used to renew the identifiers every 10 to 20 minutes is the same as for Bluetooth, no location information is used to identify potential contamination. The data that is exchanged between the different users is the ephemeral IDs of the users, the ephemeral IDs of the other people who make contact, the date, the duration of the contact and the signal strength, and this data is saved for 14 days. The application is compatible with other EU Member States, countries that are part of the European Economic Area or countries considered to have a sufficiently high data protection policy, as set out in the GDPR, that use a DP-3T infrastructure on their applications (Accord de Coopération Entre l'État Fédéral, La Communauté Fla- Mande, La Région Wallonne, La Commu- Nauté Germanophone et La Commission Communautaire Commune, 2020). When a person tests positive for Covid-19, they or a healthcare provider stores an encrypted identifier of their phone in the test server (Coronalert, n.d.). The application then checks to see if the test results are available on the test server, and if so, sends a notification with the result to the user. If the result is positive, the user can decide to download the secret codes that generated the previously distributed ephemeral identifiers to the main server, where database V is located. This download must be authorized by the test server by sending an authorization code to the main server in

order to avoid any manipulation error that could be made by a user. The data that is sent to the main server cannot be linked to a specific user. Once the secret keys are downloaded, they are deleted from the user's phone. If they are not downloaded on the main server, they remain on the user's phone for 14 days (Accord de Coopération Entre l'État Fédéral, La Communauté Fla-Mande, La Région Wallonne, La Communauté Germanophone et La Commission Communautaire Commune, 2020).

Concerns about the application

The tracing application that was introduced by several authorities around the world to help track the spread of the pandemic was not easily accepted by all citizens. According to previous research, a kind of privacy paradox has accompanied the application (Rowe, 2020; Utz et al., 2021), this paradox occurred with data privacy "versus" health and freedom. One should be compromised in favor of the other, but for the application to work properly, three conditions are identified in existing literature (Rowe, 2020). The first condition is the **accuracy** of the information about whether a person has the disease or not, but this information cannot be 100% accurate as the tests are not totally reliable. The second condition is that people who cross other people must all have their **smartphones with them**, which is not always possible, for example at the workplace people often forget their phones in their bags or on their desks. The third condition is that a high percentage of smartphone users must have **downloaded the application**, which is not always the case as downloading is not mandatory. The same concern was expressed in another paper: although the app helps stop the spread of coronavirus and provides a lot of valuable data to authorities and health researchers, it would not work if too few people download it (Fey and Hino, 2020). In this paper, it was argued that even in countries where downloading the app is mandatory, some people do not use the app or their smartphones as they should in order to avoid being "tracked". Furthermore, the authors announce that such a large amount of sensitive data has never been required by the authorities in the past. Therefore, some citizens are suspicious and make assumptions, for example, citizens in Minneapolis who participated in the Black Life Matters protests thought the police would use the contact tracing set up for Covid-19, but this was never the intention. This was a misinterpretation of what a safety commissioner said (Mullin, 2020). Other research has also shown that privacy concerns can be a barrier to downloading the app for some citizens (Utz et al., 2021). In addition, other research has shown that a high level of concern about Covid-19 actually decreases willingness to download the tracing app (Chan et Sabiq, 2021).

### 1.1.2 Covid-19 certificate - application

In Europe, the Member States have agreed to introduce a "European digital COVID certificate" (*EU Digital COVID Certificate*, n.d.), which is available since the first of July 2021, the main reason being to enable the restoration of free movement in the European union, Iceland, Liechtenstein, and Norway. A citizen can obtain this certificate in three different ways: by being fully vaccinated, by having a negative PCR test, or by proving that he or she has recovered from a previous infection with Covid-19. The different authorities in the Member States are responsible for issuing the certificate to citizens, for example via online platforms, testing centers or health authorities. The certificate will take the form of a QR code with a numeric signature, which will prevent forgery. The digital signature will be specific to the issuing organization, such as health authorities or hospitals, and the personal data will be secured in a database in each country. The personal data contained in a certificate is date the certificate was issued, name, birthdate, information about one or more of the three different ways to obtain a certificate, and a unique identifier. The QR code will be available on phone and/or paper. There will be no central European database, to verify the certificates the European commission developed a gateway, which will not let the personal data through only the validity of the certificate will be verified by checking the authority that made the certificate and signed it. Thus, each country will have its own database and the personal data will not be shared from one country to another (*EU Digital COVID Certificate*, n.d.).

In Belgium, the authorities have decided to make the certificate available in three different ways: through an application, called CovidSafeBE; through the government's existing online sites, eHealth and the site depending on where you live; and through post by calling the helpdesk specific to certification issuing (*Wil Je Reizen Binnen de EU?*, n.d.). The CovidSafeBE app is separate from Coronalert to continue to guarantee private identity on the latter (*Wil Je Reizen Binnen de EU?*, n.d.). The application was created to facilitate the lives of citizens, so all they need is their smartphone and it does not collect data unless the user allows it, the data collected is anonymous and allows to improve the performance of the application and make error reports (CovidSafeBE, n.d.). To use the application, the user must connect it with his identification to the Ehealth platform to transfer the necessary data. As a Flemish organization manages the database of vaccines in Belgium, Vaccinet, the application was created by Digitaal Vlaanderen, which is the agency responsible for the digitalization of public authorities in Flanders. The database used for the tests is called sciensano (Scharff, 2021).

| | Tracing app<br>(Coronalert, n.d.) | Certification application<br>(Privacy statement Sciensano, 2021) (Privacy disclaimer Vaccinet +, 2020) (CovidSafeBE, n.d.) | | |
|---|---|---|---|---|
| | | Test certificate | Recovery certificate | Vaccination certification |
| Date of application launch | 30 September 2020 | 16 June 2021 | | |
| How data is collected | Contact tracing is collected via a "Decentralized Privacy-Preserving Proximity Tracing" (DP-3T), the results of the tests from the Sciensano database | From database Sciensano | From database Sciensano | From database Vaccinet |
| Data on app | Secret keys, own ephemeral IDs, ephemeral IDs of others who come in contact, date, duration of contact and signal strength | Identity (Id number, first- and last name, birthdate, and principal residence)<br>Data about the test (type, name, and fabricant)<br>Covid-19 variant<br>Result of the test<br>Place and time of test | Identity (Id number, first- and last name, birthdate, principal residence)<br>Covid-19 variant person had<br>Place and date of first positive test | Identity (Id number, first- and last name, birthdate, principal residence)<br>Vaccine data (brand, lot number, Vaccine ID)<br>Place and time on vaccine |
| Creator | Sciensano | Digitaal Vlaanderen | | |
| Transfer of data | From the test server to the application<br>From one user to another (IDs)<br>From a user to the main server (secret keys) | The user can show the QR code of the application to third parties, by doing so the identity and content data of the certificates will be given.<br>Data about the use of the application and the device can be shared with the device provider. This data does not contain information about the certificate. This data sharing is in accordance with the privacy policy of https://firebase.google.com/support/privacy. | | |
| Duration of data conservation | All the data on the application is automatically erased after 14 days.<br>If the secret keys are sent to the main server in case of a positive test, the keys are immediately deleted from the application.<br>Test results are kept for 60 days after registration. | The certificates on Sciensano will be kept as long as they are valid so that the citizen can access them. The ID number and metadata will be kept for 10 years in a log database.<br>The data will be available on the application until the certificate is no longer valid or if the user deletes the application from his phone. | | Certificates will be conserved as long as they are valid so that the citizen can have access to them. On vaccinet the data will be preserved till the death of the citizen.<br>The data will be available on the application until the certificate is no longer valid or if the user deletes the application from his phone. |

*Table 2: Coronalert and CovidsafeBE comparison*

# 2 Methodology

To test the conceptual framework, a questionnaire was developed based on the case studies presented in the previous section. To analyze the questionnaire, the obtained data is divided into two databases, this way there is a distinct analysis for the two applications: Coronalert and CovidsafeBE. This section presents the questionnaire that was used, and the measurement scales chosen. Next, there will be an explanation of how we collected the data and who our respondents were.

## 2.1 Questionnaire

The approach we chose was a quantitative one, with 160 people responding to our questionnaire. The questionnaire is available in Appendix A.

To start the questionnaire, the respondent had to choose a language, French, Dutch, or English. These three languages were chosen because French and Dutch are two national languages of Belgium. German was left out because the author is not fluent in this language. Next, the respondent was introduced to the subject and purpose of the questionnaire. After that there were two filter questions. Firstly, whether the respondent lives in Belgium and secondly, whether he or she owns a smartphone. The filter questions were asked so that only people with access to Coronalert and CovidsafeBE were considered. If respondents did not answer positively to both filter questions, they were directed to the end of the questionnaire. Following this, they were asked questions on several themes. That is, trust of the government, data treatment, data theft, downloading of applications in general and how they use these applications. Then, the Coronalert application was presented. If the respondent had never heard of it, he was redirected to the next part of the questionnaire. If he answered in the affirmative, he was firstly presented with a hypothetical scenario in which he had to choose between downloading Coronalert and stopping the pandemic within a given time frame or not doing so and not stopping it. Secondly, questions were asked about the control of data on the application, the transparency regarding data treatment of the application, the perceived risks, and benefits and finally the adoption of the application. After that, the CovidsafeBE application was presented. For this application, the respondent was also asked if he/she knew it or not, otherwise he/she was redirected to the last part of the questionnaire. The other questions for CovidsafeBE followed the same structure as the Coronalert part. Finally, sociodemographic questions were asked.

## 2.2 Data collection

To collect the data, the questionnaire was posted on Facebook and LinkedIn. The social media platforms make it easy to share the questionnaire. Data collection began on July 19 and ended on July 22. The survey was conducted using Sphinx, with 160 people completing the survey and 135 people remaining after the filter questions.

## 2.3 Measurement scales

To measure the different hypotheses that were established in the previous chapter, several measurement scales were used. Multiple items were used to minimize measurement error and increase the accuracy of the evaluation. The scales and their sources are listed in Appendix B. The majority of the scales follow a 7-point Likert scale.

### 2.3.1 Dependent variables

The conceptual model has several dependent variables. The **adoption of the different applications** is measured using the two-item scale of Gao et al (2011), adapted from Davis (1989). The items were originally used to measure the adoption of mobile services but for this study they were adapted to the adoption of each of the two applications. **Perceived benefits** were measured separately for the Coronalert application and the CovidsafeBE application as they have different benefits. The structure of the measure is based on that of Forsythe et al (2006) who assessed the benefits of online shopping. For this study, the benefits were tailored to each application and 4 items were used for each application. The **perceived risks** were separated into privacy and performance risks for each application. They were based on the scales used by Featherman and Pavlou (2003) who analyzed the risks associated with the use of online services. For this study, the privacy and performance risks were adapted to the applications with 3 and 5 items respectively.

### 2.3.2 Independent variables

There are several different independent variables that influence the dependent variables. The distinction is interesting because it differently influences adoption, perceived risks, and perceived benefits (Fox, 2020). The measurement of perceived risks and benefits, which are also independent variables concerning the adoption of applications, has been explained above. **Knowledge** was measured by a 6-item scale of Çoklar and Odabasi (2009). The items initially measured knowledge about technological operations and concepts, for the purposes of this study they were adapted to knowledge about data treatment. **Experience** was measured using

a yes, no, don't know possibility regarding data theft. **Trust** was measured using the four-item scale of Kastanakis et Balabanis (2012). **Immediate benefits** were measured using Hardisty et al's (2011) choice-based binary comparisons. Initially, the items were used to measure discount rates and analyze the difference in choice with losses and gains. For our study, we chose to analyze the loss of data by downloading the application. As the benefits of each application are different, the immediate benefits were measured separately. For each application people "paid" by downloading the application to stop the pandemic or to travel freely again over seven different time periods. **Habit** was measured with the twelve-item scale of Rebar et al. (2018).

### 2.3.3 Moderators

A moderator is a variable that affects the relationship between two others, so that the effect of the independent variable on the dependent variable changes according to the value or level of the moderator (Zidda, 2020). The relation between perceived risks and the application adoption should be influenced by moderators following hypothesis H1a, H1b and H1c (c.f. 3.1.3). **Bandwagon** was measured using a three-item scale by Kastanakis et Balabanis (2012). Initially, it measured the consumption of luxury goods, for the purposes of this study it was adapted to app adoption. **Transparency** was measured using Al-Jabri and Roztocki's (2015) 7-item scale. The measurement scale was initially used to measure the transparency of enterprise resource planning systems, for the purpose of this study it was adapted to the use of Coronalert and CovidsafeBE in terms of transparency. In this context, only five of the seven items were kept. **Control** was measured using a three-item scale by Chang et al. (2015) adapted from Xu et al. (2011). Initially it measured control over private information on online banking services, for the purpose of this study it was adapted to the control over private information on the Coronalert application and the CovidsafeBE application.

## 2.4 Pre-test

A pre-test was conducted before launching the questionnaire. This was to see if the questionnaire was useable. 5 people were chosen to test the questionnaire. Each person gave feedback on the formulation and the understandability of the questions. This taught us that some sentences were not clear and had to be adapted, furthermore spelling mistakes were identified and corrected. This step also allowed us to identify the average time to fill in the questionnaire, which was 12 minutes.

## 2.5 Presentation of the sample

Our sample consists of 135 people who live in Belgium and own a smartphone. We first note that 7 respondents have never heard of Coronalert and 13 have never heard of CovidsafeBE. The questionnaire was designed in such a way that these respondents were not asked about the application they were not familiar with. For this reason, it is interesting to examine the sociodemographics of respondents who are aware of Coronalert and those who are aware of CovidsafeBE separately. Thus, the original database of 135 individuals was used to create two new ones. One with 128 respondents, to analyze the adoption, perceived benefits, and risks of Coronalert and the other with 122 respondents, to analyze the adoption, perceived benefits, and risks of CovidsafeBE. It is therefore possible that a respondent from the original database could be found in both new databases.

Four socio-demographic questions are asked in the questionnaire: gender, age, education, and occupation, this allows us to describe the sample of our questionnaire. **Gender** is assessed by asking the person to choose between “male”, “female” or “other”. **Age** is assessed by asking the respondent to classify him/herself in one of the 9 age categories. **Education** level is obtained by asking to choose between 7 options. Finally, **occupation** is established by asking participants to choose between 10 options, including the "other" option that they must specify.

Table 3 presents the socio-demographic characteristics of our respondents from both databases. We note that the majority of our respondents are female, close to 62% for both applications. The two most represented age categories in our sample are between 19 and 24 years old and between 51 and 60 years old. To find the average age of the respondents, a new variable was created with a minimum of 15.5 and a maximum of 80 years old. The calculated average is 36 years old for Coronalert and 37 years old for CovidsafeBE. All respondents have completed at least upper secondary school and are generally highly educated as the majority have a bachelor’s degree. The majority of respondents are students, which explains the overrepresentation of the age category and education level. The second most represented occupation are employees.

| | | Coronalert | | | CovidsafeBE | | |
|---|---|---|---|---|---|---|---|
| **Variable** | | **Freq** | **%** | **Cum. %** | **Freq** | **%** | **Cum. %** |
| Coronalert awareness | Aware | 128 | 100.00% | - | 118 | 96.72% | 96.72% |
| | Not aware | - | - | - | 4 | 3.28% | 100.00% |
| CovidsafeBE awareness | Aware | 118 | 92.19% | 92.19% | 122 | 100.00% | - |
| | Not aware | 10 | 7.81% | 100.00% | - | - | - |
| Gender | Female | 79 | 61.72% | 62.22% | 75 | 61.48% | 61.48% |
| | Male | 49 | 38.28% | 100.00% | 47 | 38.52% | 100.00% |
| Age | 13 – 18 years | 2 | 1.56% | 1.56% | 1 | 0.82% | 0.82% |
| | 19 – 24 years | 57 | 44.53% | 46.09% | 50 | 40.98% | 41.80% |
| | 25 – 30 years | 16 | 12.50% | 58.59% | 16 | 13.11% | 54.92% |
| | 31 – 40 years | 4 | 3.13% | 61.72% | 5 | 4.09% | 59.01% |
| | 41 – 50 years | 8 | 6.25% | 67.97% | 8 | 6.56% | 65.57% |
| | 51 – 60 years | 27 | 21.09% | 89.06% | 28 | 22.95% | 88.52% |
| | 61 – 70 years | 12 | 9.38% | 98.44% | 12 | 9.84% | 98.36% |
| | 71 years or more | 2 | 1.56% | 100.00% | 2 | 1.64% | 100.00% |
| Education | Higher secondary | 22 | 17.19% | 17.19% | 22 | 18.03% | 18.03% |
| | Bachelor | 41 | 32.03% | 49.22% | 39 | 31.97% | 50.00% |
| | Master | 64 | 50.00% | 99.22% | 60 | 49.18% | 99.18% |
| | PhD | 1 | 0.78% | 100.00% | 1 | 0.82% | 100.00% |
| Occupation | Student | 52 | 40.63% | 40.63% | 45 | 36.89% | 36.89% |
| | Employee | 27 | 21.09% | 61.72% | 28 | 22.9% | 59.84% |
| | Retired | 9 | 7.03% | 68.75% | 9 | 7.38% | 67.21% |
| | Civil servant | 17 | 13.28% | 82.03% | 17 | 13.9% | 81.15% |
| | Long-term illness | 1 | 0.78% | 82.81% | 1 | 0.82% | 81.97% |
| | Self-employed | 9 | 7.03% | 89.84% | 9 | 7.38% | 89.34% |
| | Manager | 4 | 3.13% | 92.97% | 4 | 3.27% | 92.62% |
| | Currently unemployed | 4 | 3.13% | 96.10% | 4 | 3.27% | 95.90% |
| | Disability | 3 | 2.34% | 98.44% | 3 | 2.46% | 98.36% |
| | Liberal profession | 2 | 1.56% | 100.00% | 2 | 1.64% | 100.00% |

*Table 3: Descriptive variables*

# Chapter 4: Results

In this chapter, we will analyze the different variables of our model. First, we will test the reliability of the chosen scales. Then, we will perform analysis of variance and correlation tests on our variables. Next, the correlations will be analyzed, and a multicollinearity test will be performed to ensure that our variables do not have collinearity. Finally, we will analyze the explanatory and moderating variables defined in our conceptual framework (c.f. 3.2) to determine the influence of these variables on the different dependent variables. This chapter will be divided into two parts, Coronalert and CovidsafeBE.

## 3 Coronalert

As a reminder, the database used for Coronalert consists of 128 respondents.

### 3.1 Measuring the validity and reliability of scales

It is important to measure the validity and the reliability of the scales to ensure that our scales (c.f. 2.3) represent the expected dimensions. The different items that describe a construct must be tested to ensure that the construct is presented correctly, so that the different items converge to the same response intensity. In addition, the constructs must be internally consistent (Zidda, 2020).

In order to test the validity, i.e. to verify the theoretical dimensionality of the measurement scales, an exploratory factor analysis (EFA) is performed. Two steps must be undertaken (Zidda, 2020):

- The **factor pattern table** should be analyzed so that items have a correlation greater than 0.5 to be a relevant descriptor of the factor. This means that items with a value of less than 0.5 should be eliminated.
- The **final communality estimates**, which represent the percentage of the variance of the factor by the item, should have a value higher than 0.5. Anything less than this should be deleted and the EFA analysis should start over.

To measure the reliability, **Cronbach's alpha** is used, which gives a result between 0 and 1. The higher the value of α, the more correlated the items are and therefore the internal consistency is good. For α to be deemed valid, it must be equal to or greater than 0.70. If Cronbach's alpha is between .80 and .90, it is considered ideal (Stephanie, n.d.).

The steps described were applied and are available in the Appendix D. The table 4 below shows the result of the items that should be kept. Once the scales are considered reliable and

valid, the measures used are computed based on the averages which are described in the next section.

| Variable | Items | Number of items | Cronbach's Alpha |
|---|---|---|---|
| Trust | 1. I trust my government.<br>2. The Belgian government makes truthful claims.<br>3. The Belgian government is honest.<br>~~4. I do not believe what the Belgian government tells me.~~ | 3 | 0.935850 |
| Knowledge | 1. I can explain how data treatment on applications operate.<br>2. I can use data treatment in different ways.<br>3. I can define data treatment used on applications.<br>4. I can do basic things regarding data treatment.<br>5. I can explain general concepts related to data treatment.<br>6. I can use data treatment effectively. | 6 | 0.961248 |
| Bandwagon | 1. How likely is it that you would download applications used by most people?<br>2. How likely is it that you would download applications that everyone would approve of?<br>3. How likely is it that you would download applications recognized by many people? | 3 | 0.901338 |
| Habit | 1. I do frequently.<br>2. I do automatically.<br>3. I do without having to consciously remember.<br>~~4. That makes me feel weird if I do not do it.~~<br>5. I do without thinking.<br>~~6. That would require effort not to do it.~~<br>7. That belongs to my (daily, weekly, monthly) routine.<br>8. I start doing before I realize I'm doing it.<br>~~9. I would find hard not to do.~~<br>10. I have no need to think about doing.<br>~~11. that's typically 'me'.~~<br>12. I have been doing for a long time. | 8 | 0.938326 |
| Control | 1. I believe I have control over who can get access to my personal information collected by Coronalert<br>2. I think I have control over what personal information is released by the Coronalert application<br>3. I believe I have control over how personal information is used by the Coronalert application | 3 | 0.937951 |
| Transparency | ~~1. The Coronalert application allows me to track my activities~~<br>2. Coronalert provides information on the rules and regulations of the application<br>3. Coronalert provides information about the decisions and actions of the application<br>~~4. Coronalert disseminates information on the performance of the application~~<br>~~5. Overall, Coronalert is a transparent application regarding data treatment and performance~~ | 2 | 0.849692 |
| Perceived benefits | 1. I will be informed if I have been in contact with a person who has tested positive for Covid-19<br>2. I will help to track the spread of the Covid-19 virus<br>3. On the long term I will help to stop the spread of the Covid-19 virus<br>4. Always be notified in case of possible infection | 4 | 0.858257 |
| Perceived risks | 1. What are the chances that using the Coronalert application will cause you to lose control over privacy of your location?<br>2. My downloading and using of the Coronalert application would lead to a loss of privacy for me because my personal information would be used without my knowledge<br>3. Internet hackers (criminals) might steal my private information if I used the Coronalert application | 3 | 0.834305 |
| Adoption | 1. Assuming I have access to the Coronalert application, I intend to download it.<br>2. Given that I have access to the Coronalert application, I predict that I would download it. | 2 | 0.987243 |

*Table 4: Coronalert EFA analysis*

## 3.2 Differences between the means

| Variable | Average | Std dev | Minimum | Maximum |
|---|---|---|---|---|
| Experience | 0.2188 | 0.4150 | 0 | 1 |
| Trust | 3.6017 | 1.3115 | 1 | 7 |
| Habit | 2.9981 | 1.3912 | 1 | 7 |
| Bandwagon | 2.4922 | 1.1075 | 1 | 7 |
| Knowledge | 4.0313 | 1.5778 | 1 | 7 |
| Respondents who would never download Coronalert | 0.1484 | 0.3569 | 0 | 1 |
| Respondents who would download Coronalert if the benefits were noticeable in one month or less | 0.0703 | 0.2567 | 0 | 1 |
| Respondents who would download Coronalert even if benefits are on the long term | 0.7813 | 0.4150 | 0 | 1 |
| Control regarding personal data on Coronalert | 4.6328 | 1.3727 | 1 | 7 |
| Transparency regarding data treatment on Coronalert | 3.5430 | 1.0519 | 1 | 7 |
| Perceived risks regarding data privacy on Coronalert | 3.3906 | 1.2466 | 1 | 7 |
| Perceived benefits of Coronalert | 3.0664 | 1.1749 | 1 | 7 |
| Adoption of the Coronalert application | 3.8359 | 1.9981 | 1 | 7 |

*Table 5: Coronalert means comparison*

Firstly, it is interesting to analyze table 5. As a reminder, the scales calculated were with a 7-point differential semantic scale, ranging from 1 “Strongly Agree” to 7 “Strongly Disagree” or ranging from 1 “Highly probable” to 7 “Highly improbable”. The means that are colored in green present the variables that were created (trust, habit, bandwagon, knowledge, control, transparency, perceived risks, perceived benefits, and adoption) with the average of the items in each dimension. The majority of the variables are below four (neutral), indicating that the majority of respondents agree with what was presented to them. However, the majority is also very close to four, indicating that respondents are often neutral in their responses. They generally trust the government, they recognize that using apps is a habit, they are influenceable when it comes to what the majority uses or downloads as applications, they feel that the Coronalert app is transparent in terms of data treatment, and they agree with the benefits the app provides. They also more or less agree with the perceived risks the app represent regarding data privacy, however this score is very close to neutral. They tend not to believe that the app provides control over personal data, as the score is close to five (rather disagree). The knowledge that respondents have about data processing is considered neutral as the average is very close to four (neutral). Furthermore, the score for the adoption of Coronalert is also very close to neutral. In addition, the standard deviations are low, showing that the values do not deviate much from the mean.

Furthermore, the variables colored in orange are independent variables that were not calculated using a 7-point Likert scale. The experience was calculated such that any respondent

who has had an experience with data theft and is aware of it has a value of one and anyone who has not had an experience or is not aware of it has a value of zero. As can be seen, the majority of respondents have not had experience with data theft. The immediate benefits were adapted to a categorical variable and then transformed into three dichotomous variables so that the mean and standard deviation could be analyzed. If the respondent does not want to download the app, they are placed in category 1, if the respondent agrees to download the app if the benefits are noticeable in one month or less, they are placed in category 2, and if the respondent agrees to download the app even if the benefits are only noticeable in the long term (more than one month), they are placed in category 3. We find that the majority of respondents are in category 3.

Secondly, we performed analyses of variance (ANOVA) for categorical sociodemographic variables and correlation tests for numerical sociodemographic variables. These tests can be found in the Appendix E. Each sociodemographic variable was analyzed with each dependent variable, i.e., adoption, perceived benefits, and perceived risks. We find that being female, or male, does not have a significant impact on any of the dependent variables. Education and occupation also have no significant impact on the dependent variables. Age, on the other hand, has a significant impact on the perceived benefits but not on the other two. The correlation between perceived benefits and age is 0.18004, meaning that if the age increases, the coefficient of perceived benefits also increase, which means that the perceived benefits decrease if age increases. To test among which age categories the means are significantly different an ANOVA test is performed using the original variable that measures age, which is a categorical variable with 8 different categories (0= 13-18 years old, 1= 19-24 years old, 2= 25-30 years old, 3= 31-40 years old, 4= 41-50 years old, 5= 51-60 years old, 6=61-70 years old, 7= 71+). The details of these results are available in appendix E.3 under perceived benefits. There is a significant difference between the means of age categories 6 and 1 and age categories of 6 and 2. The means of the perceived benefits differ of 1.2171 and 1.4844 respectively.

## 3.3 Correlation test and multicollinearity test

First, a correlation analysis is performed to analyze the relationship between the different variables and to see if there is collinearity between the different explanatory variables. The correlation matrix is presented in the Appendix F. For a correlation to be considered significant, its p-value must be less than 0.05. The correlation coefficient (r) has a value between -1 and +1. The closer it is to zero, the weaker the association between the variables. If r is negative, it

means that the relationship between the variables is negative, if it is positive, it is the opposite. Furthermore, r is considered high when it is greater than 0.50, medium when it is between 0.30 and 0.50 and low when it is less than 0.30 (Leard statistics, 2020). By analyzing the correlation matrix, perceived risks and trust are negatively correlated (-0.37). Knowledge is also negatively correlated with perceived risks (-0.20), however, the correlation is weak. Next to that, perceived risks are negatively correlated with adoption (-0.48). In addition, trust is positively correlated with perceived benefits (0.40). Moreover, perceived benefits are positively correlated with adoption (0.29). Finally, none of the explanatory variables were highly correlated with each other.

Secondly, a multicollinearity test was performed (SAS Institute Inc., n.d.), the analysis is in the Appendix G. The conditions to be met are the tolerance values must be greater than 0.1 and the difference of the coefficients of the eigenvalue column and the condition index column cannot differ much (Schreiber-Gregory & Jackson, 2017). No multicollinearity was identified, which allows us to move on to the next step, hypothesis analysis.

## 3.4 Hypotheses results

To be able to test the hypotheses that were established in chapter two (c.f. 3.1) three main models are used to perform multiple linear regressions. The first one analyses the explanatory variables, perceived benefits, and perceived risks (X), on the dependent variable, app adoption (Y). To do this, a top-down approach is applied, starting with a full model that analyzes all variables and then eliminating all non-significant variables, the coefficients and R-squared are then compared to analyze the evolution. Each variable is also tested independently on the dependent variable. Each regression has two control variables: age and gender, to estimate the causal effect of X on Y, however these variables will not be interpreted so that the focus remains on the variables of interest (Hünermund & Louw, 2020). The details of the regressions are available in Appendix H and the summary of the regressions are available in table 6, 7, and 8.

To test the categorical variable immediate benefits, ANOVA tests have been performed, details are available in Appendix E.1.

To analyze hypotheses H1a, H1b and H1c Hayes' process macro was used. This technique was designed by Andrew F. Hayes to easily effectuate moderation and mediation analyses (Hayes, 2017). The results are available in Appendix I.

H1 and H2

| Variables | Full model; $R^2_{Aj}$= 0.2434 | | Reg with only perceived benefits; $R^2_{Aj}$= 0.0623 | | Reg with only perceived risks; $R^2_{Aj}$= 0.2158 | |
|---|---|---|---|---|---|---|
| | Parameter estimate | Standardized estimate | Parameter estimate | Standardized estimate | Parameter estimate | Standardized estimate |
| Intercept | 5.54122 | | 2.36377 | | 6.62025 | |
| | p <.0001 | | p <.0001 | | p <.0001 | |
| Perceived benefits | 0.32287 | 0.18985 | 0.49665 | 0.29203 | | |
| | p = 0.0205 | | p =0.0011 | | | |
| Perceived risks | -0.71217 | -0.44431 | | | -0.78109 | -0.48731 |
| | p <.0001 | | | | p <.0001 | |
| Age | -0.00695 | -0.06113 | -0.00256 | -0.02252 | 0.00901 | -0.03289 |
| | p = 0.4393 | | p = 0.7970 | | p = 0.6789 | |
| Gender | -0.04606 | -0.01125 | 0.06827 | 0.01667 | 0.32297 | -0.00009332 |
| | p = 0.8850 | | p = 0.8470 | | p = 0.9991 | |

*Table 6: Coronalert regression H1 and H2*

Analyzing the multiple linear regression of hypotheses one and two, we find that the coefficient of perceived benefits has a positive sign and is significant (at the 5% level), meaning that if perceived benefits increase by one unit, Coronalert adoption increases by 0.32287. The value of perceived risks is also significant, but the sign of the coefficient is negative, meaning that if perceived risks increase by one unit, Coronalert adoption decreases by 0.44431. Looking at the other two models that represent the model with one independent variable at a time, the coefficients for perceived benefits and perceived risks increase slightly but the change is very small. Looking at the R-squared of the model with perceived risks, the variation in Coronalert adoption is explained at 21.58% while the model with only perceived benefits explains only 6.23% of this variation. Thus, the independent variable that has the greatest impact on adoption is perceived risk, which can also be seen by the coefficient in the full model. Risk and perceived benefit explain 24.34% of the variation in Coronalert adoption.

H4 and 6

| Variables | Full model; $R^2_{Aj}$= 0.1643 | | Reg with Experience | | Reg with only Trust; $R^2_{Aj}$= 0.1791 | | Reg with only Knowledge | | Reg with only Habit | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Param estimate | Std estimate | Param estimate | Std estimate | Param estimate | Std estimate | Param estimate | Std estimate | Param estimate | Std estimate |
| Intercept | 1.12316 | | Model not significant, p = 0.1484 | | 1.28063 | | Model not significant, p = 0.1150 | | Model not significant, p = 0.1435 | |
| | p = 0.0061 | | | | p = 0.0004 | | | | | |
| Experience | 0.01472 | 0.00520 | | | | | | | | |
| | p = 0.9504 | | | | | | | | | |
| Trust | 0.35902 | 0.40078 | | | 0.36398 | 0.40631 | | | | |
| | p <.0001 | | | | p <.0001 | | | | | |
| Knowledge | 0.02682 | 0.03602 | | | | | | | | |
| | p = 0.6778 | | | | | | | | | |
| Habit | 0.06372 | 0.07545 | | | | | | | | |
| | p = 0.4487 | | | | | | | | | |
| Age | 0.00955 | 0.14298 | | | 0.01277 | 0.19115 | | | | |
| | p = 0.1505 | | | | p = 0.0191 | | | | | |
| Gender | 0.20529 | 0.00068381 | | | 0.01820 | 0.00756 | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | p = 0.9936 | | p = 0.9264 | | |

*Table 7: Coronalert regression H4 and H6*

The model used to analyze part of hypotheses four and six has only one independent variable that is significant (at the 5% level). The trust that people have in their government positively influences perceived benefits, i.e. if trust increases by one, perceived benefits will increase by 0.40078. Looking at the model without the insignificant variables, thus keeping only trust and the control variables, we can see that the R-squared increases from 16.43% to 17.91%, meaning that the variation in perceived benefits is explained at 17.91% in the second case. The other regressions where non-significant variables are tested are not significant and therefore cannot be interpreted.

In order to test if immediate benefits have an impact on the perceived benefits an ANOVA test was run, the details can be seen in Appendix E.1. Immediate benefits is a categorical variable where 1= Never download the app, 2= Download when benefits are available in 1 month or less, 3= Download when benefits are available on the long term. There is a significant difference between the means of categories 2 and 3 and categories of 1 and 3. The means of the perceived benefits differ of 1.1094 and 1.0334 respectively. Which means that respondents of categories one and two perceive less benefits than respondents of category three.

H3 and 5

| **Variables** | **Full model; $R^2_{Aj}$= 0.1277** | | **Reg with Experience** | | **Reg with only Trust; $R^2_{Aj}$= 0.1338** | | **Reg with only Knowledge** | | **Reg with only Habit** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** |
| **Intercept** | 5.31120 | | Model not significant, p = 0.3059 | | 5.03609 | | Model not significant, p = 0.0899 | | Model not significant, p = 0.3862 | |
| | p <.0001 | | | | p <.0001 | | | | | |
| **Experience** | -0.04134 | -0.01376 | | | | | | | | |
| | p = 0.8720 | | | | | | | | | |
| **Trust** | -0.33208 | -0.34938 | | | -0.34909 | -0.36728 | | | | |
| | p <.0001 | | | | p <.0001 | | | | | |
| **Knowledge** | -0.09857 | -0.12476 | | | | | | | | |
| | p = 0.1605 | | | | | | | | | |
| **Habit** | -0.01910 | -0.02132 | | | | | | | | |
| | p = 0.8339 | | | | | | | | | |
| **Age** | -0.00764 | -0.10783 | | | -0.00992 | -0.13994 | | | | |
| | p = 0.2876 | | | | p = 0.0930 | | | | | |
| **Gender** | 0.02687 | 0.01052 | | | -0.04541 | -0.01778 | | | | |
| | p = 0.9041 | | | | p = 0.8325 | | | | | |

*Table 8: Coronalert regression H3 and H5*

To analyze hypotheses three and five a multiple linear regression was run. The results are summarized in the table 8 above. Again, only one independent variable can be considered significant (at the 5% level). The sign of this variable is negative, meaning that if trust increases by one unit, the perceived risks will diminish by 0.34938. When this variable is analyzed

without the other non-significant ones and with the control variables, the coefficient increases a bit. The R-squared also increases and this model explains 13.38% of the variation in perceived risks. The other regressions where non-significant variables are tested are not significant and therefore cannot be interpreted.

Immediate benefits were tested using an ANOVA test, the details of which are presented in the Appendix E.1. There is a significant difference between the means of categories three and one. The means of perceived risks differ by 1.2340. This means that respondents who download the app if the benefits are available on the long term perceive less risk on average than those who never download it.

H1a, H1b and H1c

The moderation analysis effectuated on the relation between perceived risks and adoption did not indicate that transparency, control, or bandwagon had to be considered as moderators as is shown in Appendix I. Because of this result, regressions were run to see if the three variables could be considered as independent variables regarding adoption. This is the case for transparency and control. For the regression with transparency as X and adoption as Y, the R-squared is of 0.0924, which means that 9.24% of the variation in adoption can be explained by the transparency on the app. Furthermore, if transparency increases by one unit, the adoption increases by 0.65204. For the regression with control as X and adoption as Y, the R-squared is of 0.2008, which means that 20.08% of the variation in adoption can be explained by the control user has over the personal data on the app. Furthermore, if control increases by one unit, the adoption increases by 0.11685.

# 4 CovidsafeBE

As a reminder, the database used for CovidsafeBE consists of 122 respondents.

## 4.1 Measuring the validity and reliability of scales

To measure the validity and reliability of the scales, the same stepwise design as for the Coronalert application was applied (c.f. 1.1).

The steps described were applied and are available in the Appendix K. The table 9 below shows the result of the items that should be kept. Once the scales are considered reliable and valid, the measures used are computed based on the averages which will be described in the next section.

| Variable | Items | Number of items | Cronbach's Alpha |
|---|---|---|---|
| Trust | 1. I trust my government.<br>2. The Belgian government makes truthful claims.<br>3. The Belgian government is honest.<br>~~4. I do not believe what the Belgian government tells me.~~ | 3 | 0.936379 |
| Knowledge | 1. I can explain how data treatment on applications operate.<br>2. I can use data treatment in different ways.<br>3. I can define data treatment used on applications.<br>4. I can do basic things regarding data treatment.<br>5. I can explain general concepts related to data treatment.<br>6. I can use data treatment effectively. | 6 | 0.961373 |
| Bandwagon | 1. How likely is it that you would download applications used by most people?<br>2. How likely is it that you would download applications that everyone would approve of?<br>3. How likely is it that you would download applications recognized by many people? | 3 | 0.906374 |
| Habit | 1. I do frequently.<br>2. I do automatically.<br>3. I do without having to consciously remember.<br>~~4. That makes me feel weird if I do not do it.~~<br>5. I do without thinking.<br>~~6. That would require effort not to do it.~~<br>7. That belongs to my (daily, weekly, monthly) routine.<br>8. I start doing before I realize I'm doing it.<br>~~9. I would find hard not to do.~~<br>10. I have no need to think about doing.<br>~~11. that's typically 'me'.~~<br>12. I have been doing for a long time. | 8 | 0.934800 |
| Control | 1. I believe I have control over who can get access to my personal information collected by CovidsafeBE<br>2. I think I have control over what personal information is released by the CovidsafeBE application<br>3. I believe I have control over how personal information is used by the CovidsafeBE application | 3 | 0.949304 |
| Transparency | ~~1. The CovidsafeBE application allows me to track my activities~~<br>2. CovidsafeBE provides information on the rules and regulations of the application<br>3. CovidsafeBE provides information about the decisions and actions of the application<br>4. CovidsafeBE disseminates information on the performance of the application<br>~~5. Overall, CovidsafeBE is a transparent application regarding data treatment and performance~~ | 3 | 0.886508 |
| Perceived benefits | 1. I have my certificate available on my phone<br>2. I can use the application to travel easily<br>3. I will always have my certificate at hand<br>4. I don't have to worry about forgetting my certificate in case I need it | 4 | 0.874246 |
| Perceived risks | 1. What are the chances that using the CovidsafeBE application will cause you to lose control over privacy of your medical records?<br>2. My downloading and using of the CovidsafeBE application would lead to a loss of privacy for me because my personal information would be used without my knowledge<br>3. Internet hackers (criminals) might steal my private information if I used the CovidsafeBE application | 3 | 0.875512 |
| Adoption | 1. Assuming I have access to the CovidsafeBE application, I intend to download it.<br>2. Given that I have access to the CovidsafeBE application, I predict that I would download it. | 2 | 0.975857 |

*Table 9: CovidsafeBE EFA analysis*

## 4.2 Differences between the means

| Variable | Average | Std dev | Minimum | Maximum |
|---|---|---|---|---|
| Experience | 0.2131 | 0.4112 | 0 | 1 |
| Trust | 3.5547 | 1.2667 | 1 | 7 |
| Habit | 3.0277 | 1.3860 | 1 | 7 |
| Bandwagon | 2.5301 | 1.1263 | 1 | 7 |

| | | | | |
|---|---|---|---|---|
| Knowledge | 3.9973 | 1.5856 | 1 | 7 |
| Respondents who would never download CovidsafeBE | 0.0902 | 0.2876 | 0 | 1 |
| Respondents who would download CovidsafeBE if the benefits were noticeable in one month or less | 0.0574 | 0.2335 | 0 | 1 |
| Respondents who would download CovidsafeBE even if benefits are on the long term | 0.8525 | 0.3561 | 0 | 1 |
| Control regarding personal data on Coronalert | 4.3361 | 1.3205 | 1 | 7 |
| Transparency regarding data treatment on CovidsafeBE | 3.6940 | 1.0406 | 1 | 7 |
| Perceived risks regarding data privacy on CovidsafeBE | 3.7678 | 1.3222 | 1 | 7 |
| Perceived benefits of CovidsafeBE | 2.2111 | 1.2535 | 1 | 7 |
| Adoption of CovidsafeBE | 2.3648 | 1.6615 | 1 | 7 |

*Table 10: CovidsafeBE means comparison*

Following the same structure as the interpretation of the Coronalert application, we firstly analyze table 10. As a reminder, the scales calculated were with a 7-point differential semantic scale, ranging from 1 “Strongly Agree” to 7 “Strongly Disagree” or ranging from 1 “Highly probable” to 7 “Highly improbable”. The means that are colored in green present the variables that were created (trust, habit, bandwagon, knowledge, control, transparency, perceived risks, perceived benefits, and adoption) with the average of the items in each dimension. The majority of the variables are below four (neutral), indicating that the majority of respondents agree with what was presented to them. However, the majority is also very close to four, indicating that respondents are often neutral in their responses. They generally trust the government, they recognize that using apps is a habit, they are influenceable when it comes to what the majority uses or downloads as applications, they feel that the CovidsafeBE app is transparent in terms of data treatment, and they agree with the benefits the app provides. The score of the perceived risks is close to four which means that the majority have no opinion on the risks regarding data privacy. They tend not to believe that the app provides control over personal data, but this score is very close to four (neutral). The knowledge that respondents have about data processing is considered neutral as the average is very close to four (neutral). Finally, the score for the adoption of CovidsafeBE is rather high, close to two which means that they intend to download the app. In addition, the standard deviations are low, showing that the values do not deviate much from the mean.

Furthermore, the variables colored in orange are independent variables that were not calculated using a 7-point Likert scale. As shown, the majority of respondents have not had experience with data theft. Additionally, most of the respondents agree to download the app even if the benefits are only noticeable in the long term.

Secondly, we performed analyses of variances (ANOVA) for categorical sociodemographic variables and correlation tests for numerical sociodemographic variables. These tests can be

found in the Appendix L. Each sociodemographic variable was analyzed with each dependent variable, i.e., adoption, perceived benefits, and perceived risks. We find that being female, or male, has no significant impact on the dependent variables. Age does not have a significant impact on adoption and perceived risks. Education has no significant impact on perceived benefits and perceived risks. Occupation had no impact on adoption and perceived risks.

Age has a significant impact on perceived benefits. The correlation between the two variables is 0.25146, meaning that as age increases, perceived benefits also increase. To test between which age categories the means are significantly different an ANOVA test is performed using the original variable that measures age, which is a categorical variable with 8 different categories (0= 13-18 years old, 1= 19-24 years old, 2= 25-30 years old, 3= 31-40 years old, 4= 41-50 years old, 5= 51-60 years old, 6=61-70 years old, 7= 71+). The details of these results are available in Appendix L.3 under the variation perceived benefits, there is a significant difference between the means of age categories 7 and 2 of 2.9844, between 7 and 5 of 3.2500, between 7 and 1 of 3.4350, and between 7 and 3 of 3.5250.

The ANOVA test between education (0= Higher secondary, 1= Bachelor, 2=Master, 3=PhD) and adoption is significant (see Appendix L.4). To analyze the differences between the different categories, a Tukey posthoc test is performed. The differences between category three and one, three and two, and three and zero are significant. The differences in means are 4.2179, 4.8583, and 4.9773, respectively. This means that, respondents who do not have a PhD have a higher intention to adopt CovidsafeBE than those who have one. The rather big difference in means is understandable because among the respondents, only one person has a PhD, and that person does not intend to download or use CovidsafeBE.

Occupation (0=Student, 1= Employee,2 =Retired ,3=Civil servant, 4= Long-term illness, 5= Self-employed, 6= Manager, 7= Currently unemployed, 8= Disability, 9= Liberal profession) has a significant impact on perceived benefits as can be seen in Appendix L.5. Tukey's posthoc test revealed that there were several groups that had significantly different means. The difference between current unemployed and students is 2.0167, between current unemployed and employees is 2.1071, between current unemployed and government employees is 2.1471, between retired respondents and students is 1.5722, between retired respondents and employees is 1.6627, and between retired respondents and government employees is 1.7026. Other differences between groups are not significant.

## 4.3 Correlation test and multicollinearity test

To analyze the correlation matrix the same conditions as what was used with Coronalert (c.f. 1.3) are applied here. The correlation matrix is available in Appendix M. We note that perceived risks and trust are negatively correlated (-0.45). Knowledge is also negatively correlated with perceived risks (-0.23) however, the correlation is weak. Next to that, perceived risks are negatively correlated with adoption (-0.32). In addition, trust and habit are weakly positively correlated with perceived benefits (0.24 and 0.30 respectively). Moreover, perceived benefits are highly positively correlated with adoption (0.71). Finally, none of the explanatory variables were highly correlated with each other.

Secondly, a multicollinearity test was performed (SAS Institute Inc., n.d.), the analysis is available in Appendix N. The conditions to be met are the tolerance values must be greater than 0.1 and the difference of the coefficients of the eigenvalue column and the condition index column cannot differ much (Schreiber-Gregory & Jackson, 2017). No multicollinearity was identified, which allows us to move on to the next step, hypothesis analysis.

## 4.4 Hypotheses results

To be able to test the hypotheses that were established in chapter two (c.f. 3.1) the same structure was applied as for Coronalert. The details of the different regressions are available in Appendix O. and the summary of the regressions are available in table 11, table 12, and table 13.

To test the categorical variable immediate benefits, ANOVA tests have been performed, the details are available in Appendix L.1.

To analyze hypotheses H1a, H1b and H1c Hayes' process macro was used. This technique was designed by Andrew F. Hayes to easily effectuate moderation and mediation analyses (Hayes, 2017). The results are available in Appendix P.

H1 and H2

| **Variables** | **Full model; $R^2_{Aj}$= 0.5219** | | **Reg with only perceived benefits; $R^2_{Aj}$= 0.4895** | | **Reg with only perceived risks; $R^2_{Aj}$= 0.0953** | |
|---|---|---|---|---|---|---|
| | **Parameter estimate** | **Standardized estimate** | **Parameter estimate** | **Standardized estimate** | **Parameter estimate** | **Standardized estimate** |
| **Intercept** | 1.46569 | | 0.36473 | | 3.34867 | |
| | p = 0.0025 | | p = 0.2409 | | p <0.0001 | |
| **Perceived benefits** | 0.90272 | 0.68107 | 0.94618 | 0.71386 | | |
| | p < 0.0001 | | <0.0001 | | | |
| **Perceived risks** | -0.24476 | -0.19478 | | | -0.38391 | -0.30551 |
| | p = 0.0033 | | | | p = 0.0007 | |
| **Age** | -0.00427 | -0.04520 | -0.00156 | -0.01655 | 0.00965 | 0.10223 |
| | p = 0. 4927 | | p = 0.8058 | | p = 0.2487 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Gender** | -0.02416 | -0.00711 | -0.05454 | -0.01604 | 0.16433 | 0.04833 |
| | p = 0. 9107 | | p = 0.8063 | | p = 0.5781 | |

*Table 11: CovidsafeBE regression H1 and H2*

Analyzing the multiple linear regression of hypotheses one and two, we find that the coefficient of perceived benefits has a positive sign and is significant (at the 5% level), meaning that if perceived benefits increase by one unit, CovidsafeBE adoption increases by 0.68107. The value of perceived risks is also significant, but the sign of the coefficient is negative, meaning that if perceived risks increase by one unit, CovidsafeBE adoption decreases by 0.19478. Looking at the other two models that represent the model with one independent variable at a time, the coefficients for perceived benefits and perceived risks increase but the change is small. Looking at the R-squared of the model with perceived risks, the variation in CovidsafeBE adoption is explained at 9.53% while the model with only perceived benefits explains 48.95% of this variation. Thus, the independent variable that has the greatest impact on adoption is perceived benefits, which can also be seen by the coefficient in the full model. Risk and perceived benefit explain 52.19% of the variation in Coronalert adoption.

H4 and 6

| **Variables** | **Full model; $R^2_{Aj}$= 0.1162** | | **Reg with only Experience; $R^2_{Aj}$= 0.0464** | | **Reg with only Trust; $R^2_{Aj}$= 0.0982** | | **Reg with only Knowledge; $R^2_{Aj}$= 0.0561** | | **Reg with only Habit; $R^2_{Aj}$= 0.0808** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** |
| **Intercept** | 0.3471 | | 1.4650 | | 0.6812 | | 1.1821 | | 1.1591 | |
| | p = 0.4395 | | p < 0.0001 | | p = 0.0925 | | p = 0.0014 | | p = 0.0003 | |
| **Experience** | -0.1500 | -0.0492 | -0.0974 | -0.0319 | | | | | | |
| | p = 0.5779 | | p = 0.7220 | | | | | | | |
| **Trust** | 0.2265 | 0.2289 | | | 0.2278 | 0.2302 | | | | |
| | p = 0.0114 | | | | p = 0.0097 | | | | | |
| **Knowledge** | 0.0450 | 0.0569 | | | | | 0.0855 | 0.1081 | | |
| | p = 0.5362 | | | | | | p = 0.2475 | | | |
| **Habit** | 0.1992 | 0.2202 | | | | | | | 0.2104 | 0.2326 |
| | p = 0.0441 | | | | | | | | p = 0.0350 | |
| **Age** | 0.0071 | 0.1003 | 0.0174 | 0.2439 | 0.0176 | 0.2475 | 0.0163 | 0.2291 | 0.0076 | 0.1071 |
| | p = 0.3533 | | p = 0.0073 | | p = 0.0050 | | p = 0.0121 | | p = 0.3290 | |
| **Gender** | 0.0654 | 0.0255 | 0.1888 | 0.0736 | 0.0972 | 0.0379 | 0.1241 | 0.0484 | 0.2104 | 0.0820 |
| | p = 0.7775 | | p = 0.4109 | | p = 0.6664 | | p = 0.5985 | | p = 0.3496 | |

*Table 12: CovidsafeBE regression H4 and H6*

The model used to analyze part of hypotheses four and six has two independent variable that are significant (at the 5% level). The trust that people have in their government positively influences perceived benefits, i.e., if trust increases by one, perceived benefits will increase by 0.40078. The habit of using phone applications also has a positive influence on perceived benefits, if habit increases by one unit, perceived benefits increase by 0.2202. Looking at the

regressions of each independent variable separately, they all have a significative impact on perceived benefits. The coefficients do not increase a lot when comparing to the full model. The R-squared of each regression with one independent variable is smaller than the full model. Which means that experience, trust, knowledge, and habit explain by 11,62% the variation of the perceived benefits.

The categorical variable of immediate benefits was tested using an ANOVA test, the details of which are presented in Appendix L.1. There is a significant difference between the means of categories 1 and 2 and categories of 1 and 3. The means of the perceived benefits differ by 1.7143 and 1.9832, respectively. This means that respondents who would never download CovidSafeBE, regardless of when the benefits are available, perceive less benefits than those who download the app if the benefits are available on the short or long term.

H3 and 5

| **Variables** | **Full model; $R^2_{Aj}$= 0.2425** | | **Reg with only Experience; $R^2_{Aj}$= 0.0508** | | **Reg with only Trust; $R^2_{Aj}$= 0.2261** | | **Reg with only Knowledge; $R^2_{Aj}$= 0.0603** | | **Reg with only Habit** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** | **Param estimate** | **Std estimate** |
| **Intercept** | 6.1452 | | 4.4611 | | 5.8393 | | 4.8034 | | Model not significant, p = 0.2174 | |
| | p < 0.0001 | | <.0001 | | p < 0.0001 | | p < 0.0001 | | | |
| **Experience** | -0.3813 | -0.1186 | -0.6352 | -0.1976 | | | | | | |
| | p = 0.1489 | | p = 0.0289 | | | | | | | |
| **Trust** | -0.43896 | -0.4205 | | | -0.4842 | -0.4639 | | | | |
| | p < 0.0001 | | | | p < 0.0001 | | | | | |
| **Knowledge** | -0.1234 | -0.1480 | | | | | -0.1915 | -0.2297 | | |
| | p = 0.0842 | | | | | | p = 0.0148 | | | |
| **Habit** | 0.0276 | 0.0289 | | | | | | | | |
| | p = 0.7732 | | | | | | | | | |
| **Age** | -0.0146 | -0.1941 | -0.0157 | -0.2090 | -0.0142 | -0.1894 | -0.0113 | -0.1503 | | |
| | p = 0.0538 | | p = 0.0208 | | p = 0.0197 | | p = 0.0963 | | | |
| **Gender** | 0.3581 | 0.1324 | 0.0490 | 0.0181 | 0.2974 | 0.1099 | 0.2485 | 0.0918 | | |
| | p = 0.1149 | | p = 0.8392 | | p = 0.1785 | | p = 0.3172 | | | |

*Table 13: CovidsafeBE regression H3 and H5*

To analyze hypotheses three and five, a multiple linear regression was run. The results are summarized in the table 13 above. Only one independent variable can be considered significant (at the 5% level). The sign of this variable is negative, meaning that if trust increases by one unit, the perceived risks will decrease by 0.4205. When this variable is analyzed without the other non-significant variables and with the control variables, the coefficient increases slightly. However, the R-squared does not increase, the full model has a higher R-squared. This means that experience, trust, knowledge, and habit explain 24.25% of the variation of perceived risks. The regressions that consider experience and knowledge separately are significant and each independent variable has an impact on perceived risks. If the experience of data breaches

increases by one unit, the perceived risks decrease 0.1976 and if knowledge increases by one unit, the perceived risks decrease by 0.2297. However, the R-squared of 0.0508 and 0.0603 respectively are smaller than the one of the full model. The regression that considers habit is not significant and therefore cannot be interpreted.

Immediate benefits were tested using an ANOVA test, the details of which are presented in the Appendix L.1. There is a significant difference between the means of categories three and one. The means of perceived risks differ by 1.5983. This means that respondents who download the app if the benefits are available on the long term perceive less risk on average.

H1a, H1b and H1c

The moderation analysis effectuated on the relation between perceived risks and adoption did not indicate that transparency, control, or bandwagon had to be considered. The details of this analysis are available in Appendix P. Because of this result, regressions were run to see if the three variables could be considered as independent variables regarding adoption. This is the case for bandwagon and control. For the regression with bandwagon as X and adoption as Y, the R-squared is of 0.0657, which means that 6.57% of the variation in adoption can be explained by the bandwagon effect. Furthermore, if bandwagon increases by one unit, the adoption increases by 0.41605. For the regression with control as X and adoption as Y, the R-squared is of 0.0507, which means that 5.07% of the variation in adoption can be explained by the control user has over the personal data on the app. Furthermore, if control increases by one unit, the adoption increases by 0.0164.

# Chapter 5: Discussion

The average adoption of Coronalert is very close to neutral, meaning that respondents do not really have an opinion on whether they should download the app or not. The reason behind those figures could be that the app is already outdated: it was launched in September 2020 and the questionnaire only in July 2021. By July, the pandemic was already slowing down, and "normal" life was starting to feel easier to reach. This could be why the adoption is fairly neutral. The average adoption of CovidsafeBE ranges from "agree" to "somewhat agree", meaning that, in general, respondents were ready to adopt the app. The app was launched at the end of June 2021, which means it is a very current topic. More and more people are getting vaccinated in Belgium. In addition, since the certificate is required to travel and July and August are the two vacation months in Belgium, people want to download the app so they can travel easily.

Furthermore, the average perceived benefits of Coronalert are close to the trend of agreement, meaning that respondents more or less agree that downloading the Coronalert app will allow them to be notified if they have been in contact with someone who tested positive for Covid-19. Perceived risks, on the other hand, are again very close to neutral. This means that respondents do not really know if their personal data is safe on the Coronalert app or not. For CovidsafeBE, the average of perceived benefits indicates that respondents agree with the benefits it gives, in other words respondents agree that downloading the app will make their travel easier. On the other hand, the perceived risks are very close to neutral, meaning that respondents are not sure whether their data is safe on the app or not.

The multiple regressions and ANOVA tests performed showed the influence of the different independent variables on the dependent variables. For Coronalert, hypotheses 1, 2, 3c, 4c, and 6d were validated. These hypotheses, respectively, state that the perceived benefits have a positive influence on Coronalert adoption, the perceived risks have a negative influence on Coronalert adoption, the trust in government and immediate benefits have a negative influence on perceived risk, and the trust in government and immediate benefits have a positive influence on perceived benefits. For CovidsafeBE, hypotheses 1, 2, 3c, 4c, and 6e were validated. These hypotheses respectively state that perceived benefits have a positive influence on CovidsafeBE adoption, that perceived risks have a negative influence on CovidsafeBE adoption, that trust in government has a negative influence on perceived risk, and that trust in government and habit

of using apps have a positive influence on perceived benefits. In both cases the hypotheses 3a, 3b, 4a, 4b, 5e, and 5d were rejected. They stipulate, respectively, that knowledge about data treatment and data breach experience positively influences the perceived risks of the app, that knowledge about data treatment and data breach experience negatively influences perceived benefits, and that perception of technology as a habit and immediate benefits negatively influences the perceived risks.

The **adoption of Coronalert** is mostly influenced by the perceived risks related to data privacy on the application. The data collected on the app is highly sensitive and such a large amount of it has never been requested by the government before (Fey and Hino, 2020). Therefore, it makes sense that people are more influenced by the possible risks regarding the use of the application. Furthermore, for the app to be effective in slowing the spread of coronavirus, several conditions must be met: enough people must download and use it, users must always have their phones with them, and the Covid-19 test results must be highly accurate (Rowe, 2020).

Then, the **adoption of CovidsafeBE** is mostly impacted by the perceived benefits of using the app: having a Covid-19 certificate on hand at all times. Data privacy risks also impact adoption, but this impact is less considerable, which may be explained by the fact that the certificate is available through two other channels, one of which is the ability to go to eHealth and print the certificate (CovidSafeBE, n.d.). This way, the data needed to create the certificate is not just created for the application.

**Trust in government** has the greatest impact on perceived benefits and risks for both apps. This means that if respondents trust the government, their perceived benefits of using the app increase. The impact on perceived risks is negative because if the trust increases, the perceived risks decrease. Therefore, the hypotheses are confirmed and the government, i.e., the issuing authority of the app, influences the perceived benefits and risks of the users. A similar effect is observed in apps issued by other brands or organizations (Sundar et al., 2020).

**Past experiences with data theft** did not have a significant result in the multiple regressions run on the perceived benefits and perceived risks of the two applications. This could be because the type of data theft was not specified in the questionnaire, and therefore if the data theft did

not occur on a government website or app, it may be less likely to influence the user to apply a more privacy protective behavior upon government-issued platforms. Previous research has often compared the data breach experience and the effect of behavior change within the organization where the breach occurred (Lulandala, 2020). In addition, studies have shown that 45% of the users who experienced a data breach did not change their online behavior or have an opinion on whether they changed their behavior or not (Johnson, 2021). This could explain why there is no significant impact on the perceived benefits and perceived risks.

**The perception of applications as a habit** has no influence on the perceived benefits and risks of Coronalert. The reason behind this result could be explained by the fact that Coronalert was not widely downloaded in Belgium. Thus, respondents did not consider this application as a habit (Lefevre, 2021). Therefore, it has no impact on perceived benefits or risks. By looking at CovidsafeBE, there is a significant impact of the perception of applications as a habit on the perceived benefits of the application. The application is made to ease the lives of the users by offering the possibility to always have a Covid-19 certificate with them, no printing needed (CovidSafeBE, n.d.). In this case, technology replaces printing, so it makes sense that it would have an impact on perceived benefits. However, perceived risks are not affected by the fact that apps become a habit, so we cannot conclude that users are less or more concerned about privacy risks in this case. This could be explained by the fact that the habit of using apps in general was analyzed instead of the habit of using government apps. However, this analysis would have been difficult because there are not many government applications that were used as often as Facebook for example. (MYBELGIUM, n.d.; Lulandala, 2020).

**Knowledge** does not have a significant impact on the perceived benefits and perceived risks of either application. An explanation for this is that respondents are on average close to neutral in terms of their knowledge of data processing. If they are mostly neutral, no effect can be measured on the perceived risks and perceived benefits. Removing the neutral option could have resulted in more extreme options, tending more toward agreeing or disagreeing (Nowlis et al., 2002).

The effect of **immediate benefits on perceived benefits** was tested using ANOVA. Differences in means that are significant between different categories should be interpreted in terms of the actual time it takes for the app to present benefits to the user. In the case of

Coronalert, the app was presented as a way to stop the spread of Covid-19, but because the app was not mandatory, few people downloaded it and only 2.7% of Covid-19 positive tests are reported on the app (Lefevre, 2021). This means that the conditions of enough people downloading the app, the need for users to have their phones with them at all times, and high accuracy regarding who tests positive and who does not (Rowe, 2020) are not met. Therefore, the benefits of downloading Coronalert are not available in the short term. Thus, the difference in means of perceived benefits for respondents who are sensitive to the immediacy of the benefits and respondents who would download the app even if the benefits are only available in the long term is significant. Those in the former category have a more neutral view of perceived benefits so the formulation of the hypothesis "immediate benefits positively influence the perceived benefits of using Coronalert" cannot be confirmed, however, since there are no immediate benefits, the hypothesis is possible if it is differently formulated: "Not having immediate benefits negatively influences the perceived benefits of using Coronalert". In the case of CovidsafeBE the immediate benefits are noticeable because the app allows a user to permanently have their certificate at hand once they obtained it by being fully vaccinated, having a negative covid-19 test or having a proof that they recovered from Covid-19 (CovidSafeBE, n.d.). Therefore, the difference in means of perceived benefits between people who are sensitive to the immediacy of the benefits and respondents who would never download the app is significant. However, the difference between the former category and respondents who would download the app even if the benefits are only available in the long term is not significant, therefore the hypothesis cannot be confirmed. The reason for this could be that the question was not clearly enough formulated and that respondents did not understand the hypothetical situation presented to them, which was that people would travel freely in X days/ weeks/ months after downloading the application. Another possible explanation is that the difference between people who would 'always' download the application and people who would only download it if the benefits were available on the short term is not significant because the sample is not representative enough, only 7 people belong to the former category and 104 in the latter.

Regarding the influence of **immediate benefits on perceived risks** there is no significant difference in the categories of interest. The reason why the hypothesis "immediate benefits negatively influence the perceived risks of using government health technology services" cannot be confirmed could be because the perceived risks that were evaluated in the

questionnaire were only related to data privacy. Furthermore, as was explained earlier, the immediacy of the benefits of Coronalert is not very clear at this point.

The moderation analysis conducted by using Hayes macro did not identify one of the three **moderators** as significant for the Coronalert or the CovidsafeBE application. However, when a regression is run, control and transparency are significant for Coronalert adoption and control and bandwagon for CovidsafeBE adoption. The reason why bandwagon was not considered as a moderator could be because the applications do not show who downloaded the app as is the case for social media platforms (Fu et al., 2012). The reason why control and transparency are not considered as moderators could be because the respondents are not enough aware or do not possess enough knowledge to accord importance to transparency or control (Lee & Calugar-Pop, 2020).

The different hypotheses that were validated for Coronalert are not enough to define if the privacy paradox is applied to this particular health technology service. The different theories that were tested are not conclusive, thus there is no clear sign that users do not apply a privacy protective behavior even if they intend to do so.

The hypotheses that were validated in the case of CovidsafeBE could imply that the privacy paradox is present, however, since the application was only launched at the end of June 2021 and the research was conducted a few weeks later it could be possible that only early adopters and innovators downloaded adopted the application (Meade & Rabelo, 2004). Between the 16th of June and the 2nd of August 11 million certificates were issued in Belgium and half of them were obtained by citizens through the application (Belga, 2021). Therefore, it could be that part of the early majority still had to adopt the application after the 22nd of July, the date the questionnaire ended.

# Chapter 6: Conclusions

The purpose of our research was to analyze how the privacy paradox applied to the adoption of health technology services.

In order to be able to complete this thesis, a literature search was conducted where users' privacy concerns, the privacy paradox, and the different theories surrounding it were discussed. Then, the conceptual model was created with the corresponding hypotheses. To verify this conceptual model, the case studies of Coronalert and CovidsafeBE were applied to a questionnaire that was distributed on social media. The results of this questionnaire were used to test the different hypotheses. A summary of these results will be discussed below, after that some managerial and theoretical implications will be issued.

First, we weren't able to analyze the adoption of Coronalert because the average of the respondents did not know if they would adopt it or not. Therefore, it was difficult to analyze whether the privacy paradox applied to this application. However, we were able to identify a significant impact of perceived risks and perceived benefits on the adoption of the app. We also concluded that trust in government had an impact on both perceived risks and perceived benefits, indicating that this heuristic would influence respondents' decision making. In addition, immediate benefits could also influence decision making as they have a significant outcome. Respondents who would download the app even if the benefits were available in the long term perceived more benefits than those who would only download it if the benefits were available in the short term or those who would never download it. Furthermore, respondents who download the app even if the benefits are available in the long run perceived less risks than those who would never download the app. This indicates that people who focus on the potential benefits may be making a biased decision. By analyzing the regression of perceived risks and benefits on app adoption, we can see that respondents consider risks to be more important than benefits. Therefore, it appears that citizens tried to make a rational decision by weighing the benefits and risks of the app, but because the app did not meet the requirements to work, the expected benefits of slowing the pandemic are not available. requirements were: enough people have to download the app; users should always have their phones with them; high required accuracy for who tests positive and who does not (Rowe, 2020). This may help explain why the app was not adopted. It appears that respondents do not want to risk their location information

for a benefit that does not exist. Even though the government assures that no personal information is kept (Coronalert, n.d.).

Secondly, we found that CovidsafeBE was more likely to help answer our research question, which is how the privacy paradox applies to the adoption of health technology services. Because the average adoption in our research shows that the application is adopted, furthermore a recent article showed that between June 16th and August 2nd, 11 million certificates were issued in Belgium and half of them were obtained by citizens through the application (Belga, 2021) which supports our deduction. The average in perceived benefits of the application is also more or less high, meaning that respondents consider the app as a tool for easy travel. Furthermore, the habit of using applications influences the perceived benefits, indicating that habit increases the perceived benefits and thus may cause the user to overweigh benefits when evaluating the benefits and risks to make a decision. Additionally, again, trust influenced perceived benefits and risks, which indicates that this heuristic influences the decision-making process of the respondents. In summary, at least two variables were found to influence users' decision making, indicating that users are partially influenced by the privacy paradox. Even more so when considering that the application is not the only way to obtain a Covid-19 certificate, it is also available through eHealth and by calling a helpdesk to obtain the certificate by mail (CovidSafeBE, n.d.) as the risks of sharing data through an app could be avoided by using the other two channels.

# 1 Managerial implications

This section will indicate the managerial implications to elaborate on the conclusion written in the previous section. We analyzed the privacy paradox in the context of health technology services. The results of the study have the potential of helping the government for adoption of different platforms related to health services.

First, since trust impacts the perceived benefits and risks of both apps, it is important for the government to place a lot of emphasis on the trust of its citizens in order to increase the adoption of the apps it issues. With respect to the Coronalert app launched to slow the spread of the Covid-19 virus, the government has not done enough work on citizen trust. Trust in the government could be increased by more explanation or by making a campaign to explain how the data works and that under no circumstances would they have access to personal data.

Therefore, by increasing communication, trust could increase and, as a result, the perceived benefits and perceived risks would also decrease.

Second, by looking at the point of view of the users. They weigh benefits and risks to make decisions however they do not possess all the information to make their decision. In the case of Coronalert they do not consider the benefits because there are none, however if more people downloaded and used the application it could work. Therefore, it is important that they inform themselves to increase their knowledge of the possible benefits.

## 2 Theoretical implications

This section will indicate the theoretical implications of our research based on the different results. These implications may be of interest to researchers, as the relationships highlighted can lead to further research directions.

The privacy paradox, which states that even if users don't trust social networks and the internet, they still use them, is applied to health technology services. We observed that people agree to use the CovidsafeBE application even though other channels than an application are available. Furthermore, even though respondents try to make a rational decision by considering risks and benefits, the benefits have a very high impact on the adoption of CovidsafeBE. These benefits are influenced by trust in the government and the habit of using applications. Therefore, the privacy paradox analyzed in this sector should be further analyzed in all fields of e-government.

From another perspective, this research was applied to two very specific case studies. Indeed, Coronalert and CovidsafeBE are two applications issued by the Belgian government in the context of the Covid-19 pandemic that started in 2020 and is still ongoing at the time of writing this research paper. Therefore, the analysis of the different variables that influenced the adoption of these applications can be used in future research to understand what influences users in times of crisis. In addition, this thesis can also be used by researchers studying the impact of the pandemic on technology adoption in general, as it provides the perspective of the apps issued by the Belgian government.

# 3 Limitations and suggestions for further research

This section will highlight the limitations of this research and offer some suggestions for future research.

The first limitation of this research is the choice of variables and questions used in our questionnaire. In addition, the average time respondents took to complete the questionnaire was 12 minutes, which is too long. We decided not to take into account all the theories identified to analyze the privacy paradox, the prospect theory was not used, and some theories were not fully analyzed such as cognitive heuristics, only 4 of the twelve heuristics identified by Sundar et al. (2020) were used; and underinsurance theory, past experiences and knowledge were analyzed but we did not estimate how users intended to protect their personal data (Kunreuther, 1984). Furthermore, the past experiences of data theft that were considered were in general and not analyzed specifically for applications issued by the government. However, in Belgium not a lot of applications of the government are integrated, thus analyzing this is more difficult. Furthermore, we only analyzed perceived privacy risks because we wanted to focus on privacy concerns. Moreover, some questions could have been asked differently. For example, some respondents had difficulty understanding the question about immediate benefits. Particularly, for Coronalert, some respondents did not believe in the hypothetical situation "the pandemic would slow down in X days/weeks/months if the app is downloaded", and therefore did not consider the hypothetical situation.

The second limitation is the size of our sample. Indeed, our total sample is composed of 135 people, 128 were considered for Coronalert and 122 for CovidsafeBE. It would have been better to obtain more observations to increase the representativeness of our sample. In addition, we analyzed how the privacy paradox applied to the adoption of health technology services for apps that were launched only in Belgium. Furthermore, we analyzed an app that was not adopted by Belgian citizens. Nevertheless, it was interesting to analyze how and why this app was not adopted.

The third limitation is that the chosen case studies are very new and not fully integrated by the citizens at the time of the questionnaire. Though this research allowed for a view on recent applications that were issued in the context of a crisis such as a pandemic. A generalization of the analysis of the case studies on all health technology services is not possible.

Finally, propositions for further research are to repeat a survey with a larger sample and to include all the identified theories of the privacy paradox into the research model such as the prospect theory and a more thorough application of the under-insurance theory. In addition, other platforms should be considered to analyze how the privacy paradox applies to the adoption of health technology services such as e-health. More so, e-government-issued platforms from other countries should also be considered, this would allow to analyze the impact of different political climates and mentalities. These proposals would allow for a more in-depth analysis of whether and how the privacy paradox influences users' decisions regarding government-issued applications and websites.

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# Table of illustrations

# Appendices

# Appendix A: Questionnaire

**Presentation**

Hello, my name is Soazic Delefortrie and I am Master's student in management engineering at the University of Namur. As part of my thesis, I am conducting a study on the adoption of applications launched by the government during the Covid-19 pandemic. It would be helpful and appreciated if you could answer the following questions. It will take approximately 12 minutes.

Your answers will remain anonymous and will only be used for the purposes of my thesis. Thank you in advance for your time and participation.

**Filter questions**

1) As the survey targets applications launched in Belgium, only people who live in Belgium are invited to respond.

□I live in Belgium

□I do not live in Belgium -> end of questionnaire

2) As the survey targets applications launched in Belgium, only people who live in Belgium and who own a smartphone are invited to respond.

□I have a smartphone

□I don't have a smartphone -> end of questionnaire

**General behavior**

In order to understand your behavior in relation to the following themes, please answer the next questions.

3) Thinking about the Belgian government, how do you position yourself in relation to the following questions?

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| I trust my government | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Belgian government makes truthful statements | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| The Belgian government is honest | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I don't believe what the Belgian government tells me | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

4) When thinking about data processing, how do you position yourself in relation to the following questions?

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| I can explain how data treatment on applications operate | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I can use data treatment in different ways | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I can define data treatment used on applications | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I can do basic things regarding data treatment | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I can explain general concepts related to data treatment | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I can use data treatment effectively | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

5) Have you ever experienced data theft?

□Yes

□No

□ I don't know

6) When thinking about downloading new applications, answer the questions below.

| | Very likely | Likely | Rather likely | Neutral | Rather unlikely | Unlikely | Very unlikely |
|---|---|---|---|---|---|---|---|
| How likely is it that you would download applications used by most people? | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| How likely is it that you would download applications that everyone would approve of? | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| How likely is it that you would download applications recognized by many people? | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

7) Using the applications on my phone is something...

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| I do frequently | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I do automatically | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I do without having to consciously remember | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| That makes me feel weird if I do not do it | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I do without thinking | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| That would require effort not to do it | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| That belongs to my (daily, weekly, monthly) routine | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I start doing before I realize I'm doing it | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I would find hard not to do | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I have no need to think about doing | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| that's typically 'me' | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I have been doing for a long time | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

**Coronalert**

The Coronalert app was launched around September 2020 and was introduced by the government to slow down the spread of Covid-19. The app sends a notification to the user when that person has been in contact with another who has tested positive for Covid-19.

8) Since this study analyses the adoption of applications launched by the government during the Covid-19 pandemic, it is important to know if you have heard of these applications.

□ I have already heard of Coronalert

□ I have never heard of Coronalert

9) What if we could stop the spread of the pandemic by sharing some data? Choose between sharing the data by downloading the Coronalert application and stopping the pandemic in ... time or not downloading the Coronalert application and not stopping the pandemic in ... time.

| | |
|---|---|
| Stopping the pandemic in two years | |
| Stopping the pandemic in one year | |
| Stopping the pandemic in six months | |
| Stopping the pandemic in three months | |
| Stopping the pandemic in one month | |
| Stopping the pandemic in one week | |
| Stopping the pandemic in one day | |

10) Thinking about the Coronalert application, how do you position yourself in relation to the following questions?

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| The Coronalert application allows me to track my activities | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Coronalert provides information on the rules and regulations of the application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Coronalert provides information about the decisions and actions of the application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Coronalert disseminates information on the performance of the application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Overall, Coronalert is a transparent application regarding data treatment and performance | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

11) Thinking about the Coronalert application, how do you position yourself in relation to the following questions?

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| I believe I have control over who can get access to my personal information collected by Coronalert | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I think I have control over what personal information is released by the Coronalert application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe I have control over how personal information is used by the Coronalert application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

12) Thinking about the Coronalert application, how do you position yourself in relation to the following questions?

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| I will be informed if I have been in contact with a person who has tested positive for Covid-19 | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I will help to track the spread of the Covid-19 virus | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| On the long term I will help to stop the spread of the Covid-19 virus | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I will be informed if I have been in contact with a person who has tested positive for Covid-19 | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

13) Thinking about the Coronalert application, how do you position yourself in relation to the following questions?

| | Strongly probable | Probable | Tend to be probable | Undecided | Tend to be improbable | Improbable | Strongly improbable |
|---|---|---|---|---|---|---|---|
| What are the chances that using the Coronalert application will cause you to lose control over privacy of your location/medical records? | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| My downloading and using of the Coronalert application would lead to a loss of privacy for me because my personal information would be used without my knowledge | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Internet hackers (criminals) might steal my private information if I used the Coronalert application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

14) Thinking about the Coronalert application, how do you position yourself in relation to the following questions?

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| Assuming I have access to the Coronalert application, I intend to download it | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Since I have access to the Coronalert application, I plan to download it | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

**CovidsafeBE**

The CovidsafeBE application was launched in mid-June and was introduced by the government to carry a Covid certificate with you at all times. A Covid certificate can be obtained by being vaccinated, having a negative PCR test or having proof of recovery from Covid-19. The purpose of the certificate is to allow free travel in Europe again.

15) Since this study analyses the adoption of applications launched by the government during the Covid-19 pandemic, it is important to know if you have heard of these applications.

□ I have already heard of CovidsafeBE

□ I have never heard of CovidsafeBE

16) What if people could travel freely again by downloading CovidsafeBE? Choose between sharing data by downloading the CovidsafeBE app and travelling freely in ... time or not downloading the CovidsafeBE app and not travelling freely ... time.

| | |
|---|---|
| Travelling freely in six months | |
| Travelling freely in three months | |
| Travelling freely in one month | |
| Travelling freely in two weeks | |
| Travelling freely in one week | |
| Travelling freely in one day | |
| Travel freely immediately | |

17) Thinking about the CovidsfeBE application, how do you relate to the following questions?

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| The CovidsafeBE application allows me to track my activities | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| CovidsafeBE provides information on the rules and regulations of the application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| CovidsafeBE provides information about the decisions and actions of the application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| CovidsafeBE disseminates information on the performance of the application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Overall, CovidsafeBE is a transparent application regarding data treatment and performance | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

18) Thinking about the CovidsfeBE application, how do you relate to the following question

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| I believe I have control over who can get access to my personal information collected by CovidsafeBE | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I think I have control over what personal information is released by the CovidsafeBE application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I believe I have control over how personal information is used by the CovidsafeBE application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

19) Thinking about the CovidsfeBE application, how do you relate to the following questions?

-

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| I can use the application to travel easily | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I have my certificate available on my phone | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Not having to stress about forgetting your certificate when you need it | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| I will always have my certificate at hand | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

20) Thinking about the CovidsfeBE application, how do you relate to the following questions?

| | Strongly probable | Probable | Tend to be probable | Undecided | Tend to be improbable | Improbable | Strongly improbable |
|---|---|---|---|---|---|---|---|
| What are the chances that using the CovidsafeBE application will cause me to lose control over privacy of my medical records? | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| My downloading and using of the CovidsafeBE application would lead to a loss of privacy for me because my personal information would be used without my knowledge | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| Internet hackers (criminals) might steal my private information if I used the CovidsafeBE application | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

22) Thinking about the CovidsfeBE application, how do you relate to the following questions?

**Thinking about the CovidsfeBE application, how do you relate to the following questions?**

| | Strongly agree | Agree | Tend to agree | Undecided | Tend to disagree | Disagree | Strongly disagree |
|---|---|---|---|---|---|---|---|
| Assuming I have access to the CovidsafeBE application, I intend to download it | ○ | ○ | ○ | ○ | ○ | ○ | ○ |
| As I have access to the CovidsafeBE application, I plan to download it | ○ | ○ | ○ | ○ | ○ | ○ | ○ |

## Respondent information

23) What age category do you fall into?

□ 12 years or less

□ 13 - 18 years

□ 19 - 24 years

□ 25 - 30 years

□ 31 - 40 years

□ 41- 50 years

□ 51 - 60 years

□ 61 - 70 years

□ 71 years or older

24) What is your gender?

□ Female

□ Male

□ Other

25) What is your highest level of education?

□ Elementary School

□ Lower secondary

□ Higher secondary

□ Bachelor's degree

□ Master's degree

□ PhD

□ Other

26) What is your occupation?

□ Student

□ Civil servant

□ Retired

□ Self-employed

□ Currently unemployed

□ Manager

□ Labourer

□ Liberal profession

□ Employee

□ Other

Thank you for your participation in this survey!

# Appendix B: Measurement scales

See table on next page.

| | | Items | Scale | Source |
|---|---|---|---|---|
| Adoption | Original | Intention to use<br>1. Assuming I have access to the system, I intend to download it.<br>2. Given that I have access to the system, I predict that I would download it. | 7-point Likert, strongly disagree/ agree | (Gao et al., 2011) |
| | Adaptation | 1. Assuming I have access to the Coronalert/ CovidsafeBE application, I intend to download it.<br>2. Given that I have access to the Coronalert/ CovidsafeBE application, I predict that I would download it. | 7-point Likert, strongly disagree/ agree | |
| Perceived risks | Original | Privacy risk<br>1. What are the chances that using an XXX will cause you to lose control over privacy of your payment information?<br>2. My signing up for and using an XXX would lead to a loss of privacy for me because my personal information would be used without my knowledge.<br>3. Internet hackers (criminals) might take control of my checking account if I used XXX. | 7-point Likert, improbable/ probable, strongly disagree/ agree | (Featherman & Pavlou, 2003) |
| | Adaptation | Privacy risk<br>1. What are the chances that using the Coronalert/CovidsafeBE application will cause you to lose control over privacy of your location/medical records?<br>2. My downloading and using of the Coronalert/CovidsafeBE application would lead to a loss of privacy for me because my personal information would be used without my knowledge<br>3. Internet hackers (criminals) might steal my private information if I used the Coronalert/CovidsafeBE application | 7-point Likert, highly improbable/ probable | |
| Perceived benefits | Original | Shopping Convenience<br>1. Can shop in privacy of home<br>2. I don't have to leave home<br>3. Can shop whenever I want<br>4.Can save the effort of visiting stores<br>Ease/Comfort of Shopping<br>1. Don't have to wait to be served<br>2. No hassles<br>3. Not embarrassed if you don't buy<br>4. No busy signal | 7-point Likert, strongly disagree/ agree | (Forsythe et al., 2006) |
| | Adaptation | Coronalert<br>1. I will be informed if I have been in contact with a person who has tested positive for Covid-19<br>2. I will help to track the spread of the Covid-19 virus<br>3. On the long term I will help to stop the spread of the Covid-19 virus<br>4. Always be notified in case of possible infection<br>Covidsafe<br>1. I have my certificate available on my phone | 7-point Likert, strongly disagree/ agree | |

| | | | | |
|---|---|---|---|---|
| | | 2. I can use the application to travel easily<br>3. I will always have my certificate at hand<br>4. I don't have to worry about forgetting my certificate in case I need it | | |
| Bandwagon | Original | 1. How likely is it that you would purchase/use products worn by most people?<br>2. How likely is it that you would purchase/use popular products that everyone would approve of?<br>3. How likely is it that you would purchase/use products recognized by many people? | 7-point Likert, very likely/ unlikely | (Kastanakis et Balabanis, 2012) |
| | Adaptation | 1. How likely is it that you would download applications used by most people?<br>2. How likely is it that you would download applications that everyone would approve of?<br>3. How likely is it that you would download applications recognized by many people? | 7-point Likert, very likely/ unlikely | |
| Control | Original | Perceived Control<br>1. I believe I have control over who can get access to my personal information collected by this online banking service.<br>2. I think I have control over what personal information is released by this online banking service.<br>3. I believe I have control over how personal information is used by this online banking service. | 7-point Likert, strongly disagree/ agree | (Chang et al., 2015) |
| | Adaptation | Perceived Control<br>1. I believe I have control over who can get access to my personal information collected by Coronalert/ CovidsafeBE<br>2. I think I have control over what personal information is released by the Coronalert/ CovidsafeBE application<br>3. I believe I have control over how personal information is used by the Coronalert/ CovidsafeBE application | 7-point Likert, strongly disagree/ agree | |
| Transparency | Original | Perceived information transparency (PIT)<br>1. The ERP allows me to track my activities<br>2. The ERP provides information on the organization rules and regulations<br>3. The ERP provides information about the organization decisions and actions<br>4. The ERP promotes monitoring of the organization financial expenditures<br>5. The ERP disseminates information on the organization performance<br>6. The ERP promotes openness of the organization processes, like hiring & promotion<br>7. Overall, the ERP system has enhanced transparency in my organization | 7-point Likert, strongly disagree/ agree | (Al-Jabri & Roztocki, 2015) |
| | Adaptation | Perceived information transparency<br>1. The Coronalert/ CovidsafeBE application allows me to track my activities<br>2. Coronalert/ CovidsafeBE provides information on the rules and regulations of the application<br>3. Coronalert/ CovidsafeBE provides information about the decisions and actions of the application<br>4. Coronalert/ CovidsafeBE disseminates information on the performance of the application<br>5. Overall, Coronalert/ CovidsafeBE is a transparent application regarding data treatment and performance | 7-point Likert, strongly disagree/ agree | |
| Knowledge | Original | Factor 1. Technology Operations and concepts<br>1. I can explain how technological devices operate.<br>2. I can use technological devices in different ways. | 7-point Likert, strongly disagree/ agree | (Çoklar & Odabasi, 2009) |

| | | | | |
|---|---|---|---|---|
| | | 3. I can define the technological devices found in our facility.<br>4. I can do basic things regarding computer technologies.<br>5. I can explain general concepts related to computer technology.<br>6. I can use technological devices effectively. | | |
| | Adaptation | Data treatment and concepts<br>1. I can explain how data treatment on applications operate.<br>2. I can use data treatment in different ways.<br>3. I can define data treatment used on applications.<br>4. I can do basic things regarding data treatment.<br>5. I can explain general concepts related to data treatment.<br>6. I can use data treatment effectively. | 7-point Likert, strongly disagree/ agree | |
| Trust | Original | 1. I trust _____.<br>2. _____ makes truthful claims.<br>3. _____ is honest.<br>4. I do not believe what _____ tells me. | 5- or 7-point Likert, strongly disagree/ agree | (Newell & Goldsmith, 2001) |
| | Adaptation | 1. I trust my government.<br>2. The Belgian government makes truthful claims.<br>3. The Belgian government is honest.<br>4. I do not believe what the Belgian government tells me. | 7-point Likert, strongly disagree/ agree | |
| Immediate benefits | Original | Titration, environmental loss<br>What if the improved air quality were to start one year from now?<br>1. - Receive $20 immediately - permanently improved air quality starting one year from now<br>2. - Receive $50 immediately - permanently improved air quality starting one year from now<br>3. - Receive $130 immediately - permanently improved air quality starting one year from now<br>4. - Receive $325 immediately - permanently improved air quality starting one year from now<br>5. - Receive $800 immediately - permanently improved air quality starting one year from now<br>6. - Receive $2100 immediately - permanently improved air quality starting one year from now<br>7. - Receive $5200 immediately - permanently improved air quality starting one year from now | Choose between 2 options | (Hardisty et al., 2011) |
| | Adaptation | Coronalert:<br>1. Stopping the pandemic in two years and download Coronalert or not download Coronalert<br>2. Stopping the pandemic in one year and download Coronalert or not download Coronalert<br>3. Stopping the pandemic in six months and download Coronalert or not download Coronalert<br>4. Stopping the pandemic in three months and download Coronalert or not download Coronalert<br>5. Stopping the pandemic in one month and download Coronalert or not download Coronalert<br>6. Stopping the pandemic in one week and download Coronalert or not download Coronalert<br>7. Stopping the pandemic in one day and download Coronalert or not download Coronalert<br>CovidsafeBE:<br>1. Travelling freely in six months and download CovidsafeBE or not download CovidsafeBE | Choose between 2 options | |

| | | | | |
|---|---|---|---|---|
| | | 2. Travelling freely in three months and download CovidsafeBE or not download CovidsafeBE<br>3. Travelling freely in one month and download CovidsafeBE or not download CovidsafeBE<br>4. Travelling freely in two weeks and download CovidsafeBE or not download CovidsafeBE<br>5. Travelling freely in one week and download CovidsafeBE or not download CovidsafeBE<br>6. Travelling freely in one day and download CovidsafeBE or not download CovidsafeBE<br>7. Travel freely immediately and download CovidsafeBE or not download CovidsafeBE | | |
| Habit | Original | [Behavior X] is something… -><br>1. I do frequently.<br>2. I do automatically.<br>3. I do without having to consciously remember.<br>4. That makes me feel weird if I do not do it.<br>5. I do without thinking.<br>6. That would require effort not to do it.<br>7. That belongs to my (daily, weekly, monthly) routine.<br>8. I start doing before I realize I'm doing it.<br>9. I would find hard not to do<br>10. I have no need to think about doing.<br>11. that's typically 'me'.<br>12. I have been doing for a long time. | 5 or 7-point Likert, strongly disagree/ agree | (Rebar et al., 2018) |
| | Adaptation | Using applications is something… -><br>1. I do frequently.<br>2. I do automatically.<br>3. I do without having to consciously remember.<br>4. That makes me feel weird if I do not do it.<br>5. I do without thinking.<br>6. That would require effort not to do it.<br>7. That belongs to my (daily, weekly, monthly) routine.<br>8. I start doing before I realize I'm doing it.<br>9. I would find hard not to do.<br>10. I have no need to think about doing.<br>11. that's typically 'me'.<br>12. I have been doing for a long time. | 7-point Likert, strongly disagree/ agree | |

# Appendix C: Coronalert, Descriptive statistics

| Variable | Label | N | Average | Std dev | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Z2 | Gender | 128 | 0.6171875 | 0.4879831 | 0 | 1.0000000 |
| Age | How old are you? (from 15.5 to 80 year's old) | 128 | 36.3046875 | 17.5852518 | 15.5000000 | 80.0000000 |
| Z5 | Student | 128 | 0.4062500 | 0.4930621 | 0 | 1.0000000 |
| Z6 | Employee | 128 | 0.2109375 | 0.4095772 | 0 | 1.0000000 |
| Z7 | Retired | 128 | 0.0703125 | 0.2566776 | 0 | 1.0000000 |
| Z8 | Civil servent | 128 | 0.1328125 | 0.3407055 | 0 | 1.0000000 |
| Z9 | Long-term illness | 128 | 0.0078125 | 0.0883883 | 0 | 1.0000000 |
| Z10 | Self-employed | 128 | 0.0703125 | 0.2566776 | 0 | 1.0000000 |
| Z11 | Manager | 128 | 0.0312500 | 0.1746763 | 0 | 1.0000000 |
| Z12 | Currently unemployed | 128 | 0.0312500 | 0.1746763 | 0 | 1.0000000 |
| Z13 | Disability | 128 | 0.0234375 | 0.1518829 | 0 | 1.0000000 |
| Z14 | Liberal proffesion | 128 | 0.0156250 | 0.1245069 | 0 | 1.0000000 |
| Z15 | Higher secondary | 128 | 0.1718750 | 0.3787542 | 0 | 1.0000000 |
| Z16 | Bachelor | 128 | 0.3203125 | 0.4684300 | 0 | 1.0000000 |
| Z17 | Master | 128 | 0.5000000 | 0.5019646 | 0 | 1.0000000 |
| Z18 | PhD | 128 | 0.0078125 | 0.0883883 | 0 | 1.0000000 |
| CO | Coronalert | 128 | 1.0000000 | 0 | 1.0000000 | 1.0000000 |

# Appendix D: Coronalert, Measurement scale analysis

## Appendix D.1: Trust construct

4 items

EFA:

| Factor pattern | | | |
|---|---|---|---|
| | | Factor1 | |
| TR2 | TR_true_statement | 0.91725 | |
| TR3 | TR_honest | 0.89596 | |
| TR1 | TR_trust | 0.88601 | |
| TR4i | TR_disbelief | 0.70131 | |
| Final Communality Estimates: Total = 2.920948 | | | |
| TR1 | TR2 | TR3 | TR4i |
| 0.78501688 | 0.84134244 | 0.80274729 | 0.49184158 |

EFA without TR4i:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| TR2 | TR_true_statement | 0.91879 |
| TR3 | TR_honest | 0.89625 |
| TR1 | TR_trust | 0.87685 |
| Final Communality Estimates: Total = 2.416288 | | |
| TR1 | TR2 | TR3 |
| 0.76886393 | 0.84416774 | 0.80325668 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |
| Raw | 0.935704 |

| | |
|---|---|
| Standerdized | 0.935850 |

# Appendix D.2: Knowledge construct

6 items

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| KN2 | KN_use | 0.91909 |
| KN6 | KN_ease_use | 0.91830 |
| KN5 | KN_concepts | 0.90144 |
| KN3 | KN_define | 0.89592 |
| KN1 | KN_explain | 0.89419 |
| KN4 | KN_basic | 0.85953 |

| Final Communality Estimates: Total = 4.841638 | | | | | |
|---|---|---|---|---|---|
| KN1 | KN2 | KN3 | KN4 | KN5 | KN6 |
| 0.79957720 | 0.84472497 | 0.80267498 | 0.73879171 | 0.81259780 | 0.84327152 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |
| Raw | 0.961050 |
| Standerdized | 0.961248 |

# Appendix D.3: Bandwagon construct

3 items

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| BW3 | BW_recognised | 0.87316 |
| BW2 | BW_approved | 0.84988 |
| BW1 | BW_used | 0.82073 |

| Final Communality Estimates: Total = 2.158307 | | |
|---|---|---|
| BW1 | BW2 | BW3 |
| 0.67360186 | 0.72230259 | 0.76240216 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |
| Raw | 0.900851 |
| Standerdized | 0.901338 |

# Appendix D.4: Habit construct

12 items

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| HB5 | HB_thinking | 0.86642 |

| | | |
|---|---|---|
| HB10 | HB_no_thinking | 0.83746 |
| HB2 | HB_automatic | 0.81702 |
| HB3 | HB_remember | 0.81118 |
| HB8 | HB_realize | 0.81108 |
| HB9 | HB_hard | 0.77401 |
| HB7 | HB_routine | 0.77397 |
| HB12 | HB_long_time | 0.74196 |
| HB1 | HB_often | 0.72616 |
| HB6 | HB_effort | 0.72359 |
| HB4 | HB_sensation | 0.64738 |
| HB11 | HB_typically_me | 0.59187 |

| Final Communality Estimates: Total = 7.004349 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| HB1 | HB2 | HB3 | HB4 | HB6 | HB5 | HB7 | HB8 | HB9 | HB10 | HB11 | HB12 |
| 0.52730413 | 0.66752735 | 0.65801292 | 0.41909693 | 0.52358577 | 0.75068163 | 0.59903699 | 0.65785844 | 0.59909634 | 0.70133201 | 0.35031292 | 0.55050343 |

EFA without HB4 and HB11:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| HB5 | HB_thinking | 0.87483 |
| HB2 | HB_automatic | 0.84115 |
| HB10 | HB_no_thinking | 0.83161 |
| HB3 | HB_remember | 0.81885 |
| HB8 | HB_realize | 0.79345 |
| HB7 | HB_routine | 0.78528 |
| HB1 | HB_often | 0.75756 |
| HB12 | HB_long_time | 0.75737 |
| HB9 | HB_hard | 0.74654 |
| HB6 | HB_effort | 0.68546 |

| Final Communality Estimates: Total = 6.255833 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| HB1 | HB2 | HB3 | HB5 | HB6 | HB7 | HB8 | HB9 | HB10 | HB12 |
| 0.57389060 | 0.70752736 | 0.67051723 | 0.76531965 | 0.46985187 | 0.61666468 | 0.62956880 | 0.55731927 | 0.69156842 | 0.57360474 |

EFA without HB6:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| HB5 | HB_thinking | 0.86125 |
| HB2 | HB_automatic | 0.85706 |
| HB10 | HB_no_thinking | 0.82641 |
| HB3 | HB_remember | 0.81740 |
| HB7 | HB_routine | 0.80523 |
| HB1 | HB_often | 0.78258 |
| HB12 | HB_long_time | 0.77879 |
| HB8 | HB_realize | 0.77455 |
| HB9 | HB_hard | 0.70487 |

| Final Communality Estimates: Total = 5.791477 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| HB1 | HB2 | HB3 | HB5 | HB7 | HB8 | HB9 | HB10 | HB12 |
| 0.61242439 | 0.73455253 | 0.66813661 | 0.74174715 | 0.64840309 | 0.59992023 | 0.49683474 | 0.68294854 | 0.60651009 |

EFA without HB9:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| HB2 | HB_automatic | 0.87037 |
| HB5 | HB_thinking | 0.84931 |
| HB3 | HB_remember | 0.81983 |
| HB7 | HB_routine | 0.81936 |
| HB1 | HB_often | 0.80506 |

| | | |
|---|---|---|
| HB10 | HB_no_thinking | 0.80217 |
| HB12 | HB_long_time | 0.78717 |
| HB8 | HB_realize | 0.74810 |

| Final Communality Estimates: Total = 5.293222 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **HB1** | **HB2** | **HB3** | **HB5** | **HB7** | **HB8** | **HB10** | **HB12** |
| 0.64812310 | 0.75754550 | 0.67211497 | 0.72132716 | 0.67134483 | 0.55965491 | 0.64347388 | 0.61963734 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| **Variables** | **Alpha** |
| Raw | 0.935807 |
| Standerdized | 0.938326 |

# Appendix D.5: Control construct

EFA:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| CO_C3 | Co_C_used | 0.91519 |
| CO_C2 | Co_C_released | 0.89881 |
| CO_C1 | Co_C_persons | 0.88603 |

| Final Communality Estimates: Total = 2.430482 | | |
|---|---|---|
| **CO_C1** | **CO_C2** | **CO_C3** |
| 0.78505634 | 0.80785706 | 0.83756820 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| **Variables** | **Alpha** |
| Raw | 0.937650 |
| Standerdized | 0.937951 |

# Appendix D.6: Transparency construct

EFA:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| CO_TRP3 | Co_TRP_decisions | 0.85546 |
| CO_TRP2 | Co_TRP_info_rules | 0.80474 |
| CO_TRP4 | Co_TRP_performance | 0.71142 |
| CO_TRP1 | Co_TRP_activities | 0.63009 |
| CO_TRP5 | Co_TRP_globally | 0.62195 |

| Final Communality Estimates: Total = 2.669388 | | | | |
|---|---|---|---|---|
| **CO_TRP1** | **CO_TRP2** | **CO_TRP3** | **CO_TRP4** | **CO_TRP5** |
| 0.39701967 | 0.64760430 | 0.73181433 | 0.50612438 | 0.38682517 |

EFA without CO_TRP1 and CO_TRP5:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| CO_TRP3 | Co_TRP_decisions | 0.85407 |
| CO_TRP2 | Co_TRP_info_rules | 0.78417 |
| CO_TRP4 | Co_TRP_performance | 0.66556 |

| Final Communality Estimates: Total = 1.787319 | | |
|---|---|---|
| CO_TRP2 | CO_TRP3 | CO_TRP4 |
| 0.61491679 | 0.72943553 | 0.44296686 |

EFA without CO_TRP4:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| CO_TRP3 | Co_TRP_decisions | 0.80134 |
| CO_TRP2 | Co_TRP_info_rules | 0.80134 |
| Final Communality Estimates: Total = 1.284290 | | |
| CO_TRP2 | CO_TRP3 | |
| 0.64214482 | 0.64214482 | |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |
| Raw | 0.846225 |
| Standerdized | 0.849692 |

# Appendix D.7: Perceived benefits construct

EFA:

| Factor pattern | | | |
|---|---|---|---|
| | | Factor1 | |
| CO_PB2 | Co_PB_spread | 0.80920 | |
| CO_PB1 | Co_PB_contact | 0.76434 | |
| CO_PB4 | Co_PB_notified | 0.74545 | |
| CO_PB3 | Co_PB_long_term | 0.73316 | |
| Final Communality Estimates: Total = 2.332239 | | | |
| CO_PB1 | CO_PB2 | CO_PB3 | CO_PB4 |
| 0.58421046 | 0.65480639 | 0.53752144 | 0.55570071 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |
| Raw | 0.855350 |
| Standerdized | 0.858257 |

# Appendix D.8: Perceived risks construct

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| CO_PR2 | Co_PR_loss | 0.83016 |
| CO_PR3 | Co_PR_steal | 0.73348 |
| CO_PR1 | Co_PR_control | 0.73217 |
| Final Communality Estimates: Total = 1.763233 | | |
| CO_PR1 | CO_PR2 | CO_PR3 |
| 0.53607558 | 0.68916266 | 0.53799448 |

Cronbach's Alpha :

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |

| | |
|---|---|
| Raw<br>Standerdized | 0.834687<br>0.834305 |

## Appendix D.9: Adoption construct

EFA :

| **Factor pattern** | | |
|---|---|---|
| | | **Factor1** |
| CO_AD1<br>CO_AD2 | Co_AD_intend<br>Co_AD_predict | 0.98109<br>0.98109 |
| **Final Communality Estimates: Total = 1.925056** | | |
| **CO_AD1** | **CO_AD2** | |
| 0.96252814 | 0.96252814 | |

Cronbach's Alpha :

| **Cronbach Coefficient Alpha** | |
|---|---|
| **Variables** | **Alpha** |
| Raw<br>Standerdized | 0.987243<br>0.987243 |

# Appendix E: Coronalert Analysis of variance

## Appendix E.1: Immediate benefits

Perceived benefits

Anova

| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
|---|---|---|---|---|---|
| Model | 2 | 24.5147720 | 12.2573860 | 10.16 | <.0001 |
| Error | 125 | 150.7957749 | 1.2063662 | | |

| **Level of CO_IB** | **N** | **CO_PB** | |
|---|---|---|---|
| | | **Average** | **Std dev** |
| 1 | 19 | 3.86842105 | 1.33948690 |
| 2 | 9 | 3.94444444 | 1.27951271 |
| 3 | 100 | 2.83500000 | 1.03182931 |

Tukey

| | |
|---|---|
| **Alpha** | 0.05 |
| **Degree of freedom de l'Error** | 125 |
| **Error quadratique Average** | 1.206366 |
| **Critical value of studentized range** | 3.35446 |

| **Significant comparisons at the 0.05 level indicated by ***.** | | | | |
|---|---|---|---|---|
| **CO_IB Comparison** | **Difference/between/average** | **Simultaneous 95% - Confidence interval** | | |
| 2-1 | 0.0760 | -0.9782 | 1.1302 | |
| 2-3 | 1.1094 | 0.2028 | 2.0161 | *** |
| 1-3 | 1.0334 | 0.3814 | 1.6854 | *** |

Perceived risks

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 2 | 26.0848384 | 13.0424192 | 9.52 | 0.0001 |
| Error | 125 | 171.2728005 | 1.3701824 | | |
| Corrected total | 127 | 197.3576389 | | | |

| Level of CO_IB | N | CO_PB | |
|---|---|---|---|
| | | Average | Std dev |
| 1 | 19 | 2.38596491 | 1.04387193 |
| 2 | 9 | 2.96296296 | 1.04674687 |
| 3 | 100 | 3.62000000 | 1.20140210 |

Tukey

| | |
|---|---|
| Alpha | 0.05 |
| Degree of freedom de l'Error | 125 |
| Error quadratique Average | 1.370182 |
| Critical value of studentized range | 3.35446 |

Significant comparisons at the 0.05 level indicated by ***.

| CO_IB Comparison | Difference/between/average | Simultaneous 95% - Confidence interval | | |
|---|---|---|---|---|
| 3-2 | 0.6570 | -0.3092 | 1.6233 | |
| 3-1 | 1.2340 | 0.5392 | 1.9289 | *** |
| 2-1 | 0.5770 | -0.5465 | 1.7005 | |

# Appendix E.2: Gender

Adoption

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 1 | 0.8137937 | 0.8137937 | 0.20 | 0.6534 |
| Error | 126 | 506.2408938 | 4.0177849 | | |
| Corrected total | 127 | 507.0546875 | | | |

Perceived benefits

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 1 | 1.1919406 | 1.1919406 | 0.86 | 0.3548 |
| Error | 126 | 174.1186063 | 1.3818937 | | |
| Corrected total | 127 | 175.3105469 | | | |

Perceived risks

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 1 | 1.4082718 | 1.4082718 | 0.91 | 0.3431 |

| | | | | | |
|---|---|---|---|---|---|
| Error<br>Corrected total | 126<br>127 | 195.9493671<br>197.3576389 | 1.5551537 | | |

# Appendix E.3: Age

## Adoption

Pearson correlation

| Pearson correlation coefficients, N = 128<br>Prob > \|r\| under H0: Rho=0 | | |
|---|---|---|
| | **Age** | **CO_AD** |
| **Age**<br>**How old are you? (from 15.5 to 80 year's old)** | 1.00000 | 0.03057<br>0.7320 |
| **CO_AD**<br>**Adoption of the Coronalert application** | 0.03057<br>0.7320 | 1.00000 |

## Perceived benefits

Pearson correlation

| Pearson correlation coefficients, N = 128<br>Prob > \|r\| under H0: Rho=0 | | |
|---|---|---|
| | **Age** | **CO_PB** |
| **Age**<br>**How old are you? (from 15.5 to 80 year's old)** | 1.00000 | 0.18004<br>0.0420 |
| **CO_PB**<br>**Perceived benefits of Coronalert** | 0.18004<br>0.0420 | 1.00000 |

ANOVA test

| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
|---|---|---|---|---|---|
| Model | 7 | 23.4516516 | 3.3502359 | 2.65 | 0.0140 |
| Error | 120 | 151.8588953 | 1.2654908 | | |
| Corrected total | 127 | 175.3105469 | | | |

| **Level of CO_IB** | **N** | **CO_PB** | |
|---|---|---|---|
| | | **Average** | **Std dev** |
| 0 | 2 | 4.50000000 | 0.70710678 |
| 1 | 57 | 2.90789474 | 1.07698278 |
| 2 | 16 | 2.64062500 | 1.18662248 |
| 3 | 4 | 3.62500000 | 1.01036297 |
| 4 | 8 | 3.09375000 | 0.39949745 |
| 5 | 27 | 2.97222222 | 1.09705316 |
| 6 | 12 | 4.12500000 | 1.61491627 |
| 7 | 2 | 3.25000000 | 1.06066017 |

| | |
|---|---|
| **Alpha** | 0.05 |
| **Degree of freedom de l'Error** | 120 |
| **Error quadratique Average** | 1.265491 |
| **Critical value of studentized range** | 4.36297 |

| **Significant comparisons at the 0.05 level indicated by ***.** | | | | |
|---|---|---|---|---|
| **CO_IB Comparison** | **Difference/between/average** | **Simultaneous 95% - Confidence interval** | | |
| 0 - 6 | 0.3750 | -2.2757 | 3.0257 | |
| 0 - 3 | 0.8750 | -2.1306 | 3.8806 | |

| | | | | |
|---|---|---|---|---|
| 0 - 7 | 1.2500 | -2.2205 | 4.7205 | |
| 0 - 4 | 1.4063 | -1.3374 | 4.1499 | |
| 0 - 5 | 1.5278 | -1.0155 | 4.0711 | |
| 0 - 1 | 1.5921 | -0.9046 | 4.0888 | |
| 0 - 2 | 1.8594 | -0.7435 | 4.4623 | |
| 6 - 3 | 0.5000 | -1.5037 | 2.5037 | |
| 6 - 7 | 0.8750 | -1.7757 | 3.5257 | |
| 6 - 4 | 1.0313 | -0.5528 | 2.6153 | |
| 6 - 5 | 1.1528 | -0.0513 | 2.3569 | |
| 6 - 1 | 1.2171 | 0.1148 | 2.3194 | *** |
| 6 - 2 | 1.4844 | 0.1590 | 2.8097 | *** |
| 3 - 7 | 0.3750 | -2.6306 | 3.3806 | |
| 3 - 4 | 0.5313 | -1.5940 | 2.6565 | |
| 3 - 5 | 0.6528 | -1.2066 | 2.5121 | |
| 3 - 1 | 0.7171 | -1.0780 | 2.5122 | |
| 3 - 2 | 0.9844 | -0.9557 | 2.9245 | |
| 7 - 4 | 0.1563 | -2.5874 | 2.8999 | |
| 7 - 5 | 0.2778 | -2.2655 | 2.8211 | |
| 7 - 1 | 0.3421 | -2.1546 | 2.8388 | |
| 7 - 2 | 0.6094 | -1.9935 | 3.2123 | |
| 4 - 5 | 0.1215 | -1.2755 | 1.5186 | |
| 4 - 1 | 0.1859 | -1.1244 | 1.4962 | |
| 4 - 2 | 0.4531 | -1.0497 | 1.9559 | |
| 5 - 1 | 0.0643 | -0.7465 | 0.8751 | |
| 5 - 2 | 0.3316 | -0.7633 | 1.4265 | |
| 1 - 2 | 0.2673 | -0.7146 | 1.2492 | |

Perceived risks

Pearson correlation

| **Pearson correlation coefficients, N = 128**<br>**Prob > \|r\| under H0: Rho=0** | | |
|---|---|---|
| | **Age** | **CO_PR** |
| **Age**<br>**How old are you? (from 15.5 to 80 year's old)** | 1.00000 | -0.13023<br>0.1429 |
| **CO_PR**<br>**Perceived risks of Coronalert** | -0.13023<br>0.1429 | 1.00000 |

# Appendix E.4: Education

Adoption

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 3 | 12.7651573 | 4.2550524 | 1.07 | 0.3655 |
| Error | 124 | 494.2895302 | 3.9862059 | | |
| Corrected total | 127 | 507.0546875 | | | |

Perceived benefits

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 3 | 7.0305701 | 2.3435234 | 1.73 | 0.1649 |
| Error | 124 | 168.2799768 | 1.3570966 | | |
| Corrected total | 127 | 175.3105469 | | | |

Perceived risks

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 3 | 9.3446854 | 3.1148951 | 2.05 | 0.1097 |
| Error | 124 | 188.0129535 | 1.5162335 | | |
| Corrected total | 127 | 197.3576389 | | | |

# Appendix E.5: Occupation

Adoption

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 9 | 19.5044424 | 2.1671603 | 0.52 | 0.8543 |
| Error | 118 | 487.5502451 | 4.1317817 | | |
| Corrected total | 127 | 507.0546875 | | | |

Perceived benefits

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 9 | 16.1070029 | 1.7896670 | 1.33 | 0.2305 |
| Error | 118 | 159.2035440 | 1.3491826 | | |
| Corrected total | 127 | 175.3105469 | | | |

Perceived risks

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 9 | 10.4449804 | 1.1605534 | 0.73 | 0.6782 |
| Error | 118 | 186.9126585 | 1.5840056 | | |
| Corrected total | 127 | 197.3576389 | | | |

# Appendix F: Coronalert, Descriptive statistics and correlation

| Variable | Label | Average | Std dev | Minimum | Maximum |
|---|---|---|---|---|---|
| Exp | Experience | 0.2187500 | 0.4150230 | 0 | 1 |
| CO_TR | Trust | 3.6015625 | 1.3115401 | 1 | 7 |
| CO_HB | Habit | 2.9980469 | 1.3912324 | 1 | 7 |
| CO_BW | Bandwagon | 2.4921875 | 1.1074905 | 1 | 7 |
| CO_KN | Knowledge | 4.0312500 | 1.5777807 | 1 | 7 |
| IB_Cat1 | Respondents who would never download Coronalert | 0.1484375 | 0.3569301 | 0 | 1 |
| IB_Cat2 | Respondents who would download Coronalert if the benefits were noticeable in one month or less | 0.0703125 | 0.2566776 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| IB_Cat3 | Respondents who would download Coronalert even if benefits are on the long term | 0.7812500 | 0.4150230 | 0 | 1 |
| CO_C | Control over Coronalert | 4.6328125 | 1.3726741 | 1 | 7 |
| CO_TRP | Transparency regarding Coronalert | 3.5429688 | 1.0518588 | 1 | 7 |
| CO_PR | Perceived risks regarding data privacy on Coronalert | 3.3906250 | 1.2465942 | 1 | 7 |
| CO_PB | Perceived benefits of Coronalert | 3.0664063 | 1.1749034 | 1 | 7 |
| CO_AD | Adoption of the Coronalert application | 3.8359375 | 1.9981383 | 1 | 7 |
| Age | How old are you? (from 15.5 to 80 year's old) | 36.3046875 | 17.5852518 | 15.5 | 80 |
| Z2 | Gender | 0.6171875 | 0.4879831 | 0 | 1 |
| Z5 | Student | 0.4062500 | 0.4930621 | 0 | 1 |
| Z6 | Employee | 0.2109375 | 0.4095772 | 0 | 1 |
| Z7 | Retired | 0.0703125 | 0.2566776 | 0 | 1 |
| Z8 | Civil servent | 0.1328125 | 0.3407055 | 0 | 1 |
| Z9 | Long-term illness | 0.0078125 | 0.0883883 | 0 | 1 |
| Z10 | Self-employed | 0.0703125 | 0.2566776 | 0 | 1 |
| Z11 | Manager | 0.0312500 | 0.1746763 | 0 | 1 |
| Z12 | Currently unemployed | 0.0312500 | 0.1746763 | 0 | 1 |
| Z14 | Liberal proffesion | 0.0156250 | 0.1245069 | 0 | 1 |
| Z15 | Higher secondary | 0.1718750 | 0.3787542 | 0 | 1 |
| Z16 | Bachelor | 0.3203125 | 0.4684300 | 0 | 1 |
| Z17 | Master | 0.5000000 | 0.5019646 | 0 | 1 |
| Z18 | PhD | 0.0078125 | 0.0883883 | 0 | 1 |

**Pearson correlation coefficients, N = 128**
**Prob > |r| under H0: Rho=0**

| | Exp | CO_TR | CO_HB | CO_KN | CO_PR | CO_PB | CO_AD | Age | Z2 |
|---|---|---|---|---|---|---|---|---|---|
| Exp<br>Experience | 1.00000 | 0.14692<br>0.0979 | -0.16120<br>0.0691 | 0.02756<br>0.7575 | -0.05485<br>0.5386 | 0.03860<br>0.6653 | 0.03887<br>0.6631 | -0.09983<br>0.2622 | -0.04981<br>0.5766 |
| CO_TR<br>Trust | 0.14692<br>0.0979 | 1.00000 | -0.01625<br>0.8555 | 0.16144<br>0.0687 | -0.36639<br><.0001 | 0.40225<br><.0001 | 0.47713<br><.0001 | -0.02792<br>0.7544 | 0.16990<br>0.0552 |
| CO_HB<br>Habit | -0.16120<br>0.0691 | -0.01625<br>0.8555 | 1.00000 | 0.15039<br>0.0902 | -0.09282<br>0.2974 | 0.15393<br>0.0828 | 0.18701<br>0.0345 | 0.56239<br><.0001 | 0.00034<br>0.9970 |
| CO_KN<br>Knowledge | 0.02756<br>0.7575 | 0.16144<br>0.0687 | 0.15039<br>0.0902 | 1.00000 | -0.20086<br>0.0230 | 0.13745<br>0.1218 | 0.19083<br>0.0309 | 0.17527<br>0.0478 | 0.26452<br>0.0026 |
| CO_PR<br>Perceived risks regarding data privacy on Coronalert | -0.05485<br>0.5386 | -0.36639<br><.0001 | -0.09282<br>0.2974 | -0.20086<br>0.0230 | 1.00000 | -0.25082<br>0.0043 | -0.48301<br><.0001 | -0.13023<br>0.1429 | -0.08447<br>0.3431 |
| CO_PB<br>Perceived benefits of Coronalert | 0.03860<br>0.6653 | 0.40225<br><.0001 | 0.15393<br>0.0828 | 0.13745<br>0.1218 | -0.25082<br>0.0043 | 1.00000 | 0.28935<br>0.0009 | 0.18004<br>0.0420 | 0.08246<br>0.3548 |
| CO_AD<br>Adoption of the Coronalert application | 0.03887<br>0.6631 | 0.47713<br><.0001 | 0.18701<br>0.0345 | 0.19083<br>0.0309 | -0.48301<br><.0001 | 0.28935<br>0.0009 | 1.00000 | 0.03057<br>0.7320 | 0.04006<br>0.6534 |
| Age<br>How old are you? (from 15.5 to 80 year's old) | -0.09983<br>0.2622 | -0.02792<br>0.7544 | 0.56239<br><.0001 | 0.17527<br>0.0478 | -0.13023<br>0.1429 | 0.18004<br>0.0420 | 0.03057<br>0.7320 | 1.00000 | 0.03067<br>0.7311 |
| Z2<br>Gender | -0.04981<br>0.5766 | 0.16990<br>0.0552 | 0.00034<br>0.9970 | 0.26452<br>0.0026 | -0.08447<br>0.3431 | 0.08246<br>0.3548 | 0.04006<br>0.6534 | 0.03067<br>0.7311 | 1.00000 |

# Appendix G: Coronalert, Multicollinearity test

Adoption: Variance Inflation Factor and Tolerance

**Parameter estimates**

| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Tolerance | Variance inflation |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Intercept** | Intercept | 1 | 5.54122 | 0.77612 | 7.14 | <.0001 | . | 0 |
| **CO_PR** | Perceived risks regarding data privacy on Coronalert | 1 | -0.71217 | 0.12859 | -5.54 | <.0001 | 0.92569 | 1.08028 |
| **CO_PB** | Perceived benefits of Coronalert | 1 | 0.32287 | 0.13749 | 2.35 | 0.0205 | 0.91157 | 1.09701 |
| **Age** | How old are you? (From 15.5 to 80 year's old) | 1 | -0.00695 | 0.00895 | -0.78 | 0.4393 | 0.95976 | 1.04193 |
| **Z2** | Gender | 1 | -0.04606 | 0.31784 | -0.14 | 0.8850 | 0.98875 | 1.01137 |

| **Collinearity diagnostic** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Proportion of variation** | | | | | |
| **Number** | **Eigenvalue** | **Condition index** | **Intercept** | **CO_PR** | **CO_PB** | **Age** | **Z2** |
| 1 | 4.32485 | 1.00000 | 0.00202 | 0.00511 | 0.00558 | 0.00837 | 0.01460 |
| 2 | 0.33749 | 3.57978 | 0.00275 | 0.02073 | 0.00769 | 0.03610 | 0.92282 |
| 3 | 0.18228 | 4.87099 | 0.00499 | 0.30934 | 0.03924 | 0.39767 | 0.00003474 |
| 4 | 0.12670 | 5.84239 | 0.00198 | 0.05038 | 0.55939 | 0.45259 | 0.02184 |
| 5 | 0.02867 | 12.28112 | 0.98826 | 0.61444 | 0.38809 | 0.10527 | 0.04071 |

Perceived benefits: Variance Inflation Factor and Tolerance

| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Tolerance** | **Variance inflation** |
|---|---|---|---|---|---|---|---|---|
| **Intercept** | Intercept | 1 | 1.12316 | 0.40241 | 2.79 | 0.0061 | . | 0 |
| **CO_TR** | Trust | 1 | 0.35902 | 0.07527 | 4.77 | <.0001 | 0.93217 | 1.07277 |
| **CO_HB** | Habit | 1 | 0.06372 | 0.08384 | 0.76 | 0.4487 | 0.66764 | 1.49781 |
| **CO_KN** | Knowledge | 1 | 0.02682 | 0.06440 | 0.42 | 0.6778 | 0.87983 | 1.13658 |
| **Exp** | Experience | 1 | 0.01472 | 0.23623 | 0.06 | 0.9504 | 0.94501 | 1.05819 |
| **Age** | How old are you? (from 15.5 to 80 year's old) | 1 | 0.00955 | 0.00660 | 1.45 | 0.1505 | 0.67392 | 1.48385 |
| **Z2** | Gender | 1 | 0.00165 | 0.20529 | 0.01 | 0.9936 | 0.90515 | 1.10479 |

| **Collinearity diagnostic** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Proportion of variation** | | | | | | | |
| **Number** | **Eigenvalue** | **Condition index** | **Intercept** | **CO_TR** | **CO_HB** | **CO_KN** | **Exp** | **Age** | **Z2** |
| **1** | 5.47595 | 1.00000 | 0.00177 | 0.00326 | 0.00340 | 0.00353 | 0.00663 | 0.00367 | 0.00817 |
| **2** | 0.78549 | 2.64034 | 0.00012442 | 0.00001283 | 0.00433 | 0.00050526 | 0.86944 | 0.00343 | 0.00866 |
| **3** | 0.35265 | 3.94053 | 0.00123 | 0.00009796 | 0.04436 | 0.00011080 | 0.00002657 | 0.04543 | 0.71975 |
| **4** | 0.16364 | 5.78481 | 0.02218 | 0.24985 | 0.08183 | 0.06141 | 0.11048 | 0.17315 | 0.23282 |
| **5** | 0.10077 | 7.37153 | 0.00235 | 0.28883 | 0.03249 | 0.79604 | 0.00053069 | 0.00017531 | 0.02774 |
| **6** | 0.07874 | 8.33917 | 0.00004048 | 0.02542 | 0.76599 | 0.00406 | 0.00977 | 0.74963 | 0.00283 |
| **7** | 0.04275 | 11.31728 | 0.97230 | 0.43253 | 0.06759 | 0.13435 | 0.00312 | 0.02451 | 0.00002541 |

Perceived risks: Variance Inflation Factor and Tolerance

| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Tolerance** | **Variance inflation** |
|---|---|---|---|---|---|---|---|---|
| **Intercept** | Intercept | 1 | 5.31120 | 0.43620 | 12.18 | <.0001 | . | 0 |
| **CO_TR** | Trust | 1 | -0.33208 | 0.08159 | -4.07 | <.0001 | 0.93217 | 1.07277 |
| **CO_HB** | Habit | 1 | -0.01910 | 0.09088 | -0.21 | 0.8339 | 0.66764 | 1.49781 |
| **CO_KN** | Knowledge | 1 | -0.09857 | 0.06981 | -1.41 | 0.1605 | 0.87983 | 1.13658 |
| **Exp** | Experience | 1 | -0.04134 | 0.25607 | -0.16 | 0.8720 | 0.94501 | 1.05819 |
| **Age** | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00764 | 0.00716 | -1.07 | 0.2876 | 0.67392 | 1.48385 |
| **Z2** | Gender | 1 | 0.02687 | 0.22253 | 0.12 | 0.9041 | 0.90515 | 1.10479 |

| **Collinearity diagnostic** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Proportion of variation** | | | | | | | |
| **Number** | **Eigenvalue** | **Condition index** | **Intercept** | **CO_TR** | **CO_HB** | **CO_KN** | **Exp** | **Age** | **Z2** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 5.47595 | 1.00000 | 0.00177 | 0.00326 | 0.00340 | 0.00353 | 0.00663 | 0.00367 | 0.00817 |
| **2** | 0.78549 | 2.64034 | 0.00012442 | 0.00001283 | 0.00433 | 0.00050526 | 0.86944 | 0.00343 | 0.00866 |
| **3** | 0.35265 | 3.94053 | 0.00123 | 0.00009796 | 0.04436 | 0.00011080 | 0.00002657 | 0.04543 | 0.71975 |
| **4** | 0.16364 | 5.78481 | 0.02218 | 0.24985 | 0.08183 | 0.06141 | 0.11048 | 0.17315 | 0.23282 |
| **5** | 0.10077 | 7.37153 | 0.00235 | 0.28883 | 0.03249 | 0.79604 | 0.00053069 | 0.00017531 | 0.02774 |
| **6** | 0.07874 | 8.33917 | 0.00004048 | 0.02542 | 0.76599 | 0.00406 | 0.00977 | 0.74963 | 0.00283 |
| **7** | 0.04275 | 11.31728 | 0.97230 | 0.43253 | 0.06759 | 0.13435 | 0.00312 | 0.02451 | 0.00002541 |

# Appendix H: Coronalert, regressions

## Appendix H.1: Model 1

Model 1: DV= Adoption, IV= Perceived benefits, IV= perceived risks, CV= Age and gender

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 4 | 135.49560 | 33.87390 | 11.21 | <.0001 |
| **Error** | 123 | 371.55909 | 3.02081 | | |
| **Corrected total** | 127 | 507.05469 | | | |
| **Root MSE** | 1.73805 | **R-square** | 0.2672 | | |
| **Dependent mean** | 3.83594 | **R-square adj.** | 0.2434 | | |
| **Coeff Var** | 45.30956 | | | | |

| **Estimated parameters** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 5.54122 | 0.77612 | 7.14 | <.0001 | 0 |
| CO_PR | Perceived risks regarding data privacy on Coronalert | 1 | -0.71217 | 0.12859 | -5.54 | <.0001 | -0.44431 |
| CO_PB | Perceived benefits of Coronalert | 1 | 0.32287 | 0.13749 | 2.35 | 0.0205 | 0.18985 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00695 | 0.00895 | -0.78 | 0.4393 | -0.06113 |
| Z2 | Gender | 1 | -0.04606 | 0.31784 | -0.14 | 0.8850 | -0.01125 |

Individual regressions

Perceived benefits -> Adoption

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 42.83569 | 14.27856 | 3.81 | 0.0118 |
| **Error** | 124 | 464.21899 | 3.74370 | | |
| **Corrected total** | 127 | 507.05469 | | | |
| **Root MSE** | 1.93486 | **R-square** | 0.0845 | | |
| **Dependent mean** | 3.83594 | **R-square adj.** | 0.0623 | | |
| **Coeff Var** | 50.44047 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 2.36377 | 0.58190 | 4.06 | <.0001 | 0 |
| CO_PB | Perceived benefits of Coronalert | 1 | 0.49665 | 0.14902 | 3.33 | 0.0011 | 0.29203 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00256 | 0.00993 | -0.26 | 0.7970 | -0.02252 |
| Z2 | Gender | 1 | 0.06827 | 0.35309 | 0.19 | 0.8470 | 0.01667 |

Perceived risks -> Adoption

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 118.83674 | 39.61225 | 12.65 | <.0001 |
| **Error** | 124 | 388.21795 | 3.13079 | | |
| **Corrected total** | 127 | 507.05469 | | | |
| **Root MSE** | 1.76940 | **R-square** | 0.2344 | | |
| **Dependent mean** | 3.83594 | **R-square adj.** | 0.2158 | | |
| **Coeff Var** | 46.12702 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 6.62025 | 0.63678 | 10.40 | <.0001 | 0 |
| CO_PR | Perceived risks regarding data privacy on Coronalert | 1 | -0.78109 | 0.12745 | -6.13 | <.0001 | -0.48731 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00374 | 0.00901 | -0.41 | 0.6789 | -0.03289 |
| Z2 | Gender | 1 | -0.00038213 | 0.32297 | -0.00 | 0.9991 | -0.00009332 |

# Appendix H.2: Model 2

Model 2: DV= Perceived benefits, IV= Experience, Trust, Knowledge, Habit, CV= Age and gender

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 6 | 35.72426 | 5.95404 | 5.16 | <.0001 |
| **Error** | 121 | 139.58628 | 1.15361 | | |
| **Corrected total** | 127 | 175.31055 | | | |
| **Root MSE** | 1.07406 | **R-square** | 0.2038 | | |
| **Dependent mean** | 3.06641 | **R-square adj.** | 0.1643 | | |
| **Coeff Var** | 35.02668 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | Intercept | 1 | 1.12316 | 0.40241 | 2.79 | 0.0061 | 0 |
| Exp | Experience | 1 | 0.01472 | 0.23623 | 0.06 | 0.9504 | 0.00520 |
| CO_TR | Trust | 1 | 0.35902 | 0.07527 | 4.77 | <.0001 | 0.40078 |
| CO_KN | Knowledge | 1 | 0.02682 | 0.06440 | 0.42 | 0.6778 | 0.03602 |
| CO_HB | Habit | 1 | 0.06372 | 0.08384 | 0.76 | 0.4487 | 0.07545 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.00955 | 0.00660 | 1.45 | 0.1505 | 0.14298 |
| Z2 | Gender | 1 | 0.00165 | 0.20529 | 0.01 | 0.9936 | 0.00068381 |

Individual regressions

Experience -> Perceived benefits

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 7.36375 | 2.45458 | 1.81 | 0.1484 |
| **Error** | 124 | 167.94680 | 1.35441 | | |
| **Corrected total** | 127 | 175.31055 | | | |

Trust -> Perceived benefits

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 34.79477 | 11.59826 | 10.24 | <.0001 |
| **Error** | 124 | 140.51578 | 1.13319 | | |
| **Corrected total** | 127 | 175.31055 | | | |
| **Root MSE** | 1.06451 | **R-square** | 0.1985 | | |
| **Dependent mean** | 3.06641 | **R-square adj.** | 0.1791 | | |
| **Coeff Var** | 34.71539 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 1.28063 | 0.34911 | 3.67 | 0.0004 | 0 |
| CO_TR | Trust | 1 | 0.36398 | 0.07313 | 4.98 | <.0001 | 0.40631 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.01277 | 0.00538 | 2.38 | 0.0191 | 0.19115 |
| Z2 | Gender | 1 | 0.01820 | 0.19656 | 0.09 | 0.9264 | 0.00756 |

Knowledge -> Perceived benefits

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 8.15643 | 2.71881 | 2.02 | 0.1150 |
| **Error** | 124 | 167.15412 | 1.34802 | | |
| **Corrected total** | 127 | 175.31055 | | | |

Habit -> Perceived benefits

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | | | **F value** | **Pr > F** |

| | | Sum of squares | Medium square | | |
|---|---|---|---|---|---|
| **Model** | 3 | 7.46852 | 2.48951 | 1.84 | 0.1435 |
| **Error** | 124 | 167.84203 | 1.35356 | | |
| **Corrected total** | 127 | 175.31055 | | | |

# Appendix H.3: Model 3

Model 3: DV= Perceived risks, IV= Experience, Trust, Knowledge, Habit, CV= Age and gender

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 6 | 33.34483 | 5.55747 | 4.10 | 0.0009 |
| **Error** | 121 | 164.01281 | 1.35548 | | |
| **Corrected total** | 127 | 197.35764 | | | |
| **Root MSE** | 1.16425 | **R-square** | 0.1690 | | |
| **Dependent mean** | 3.39063 | **R-square adj.** | 0.1277 | | |
| **Coeff Var** | 34.33732 | | | | |

| **Estimated parameters** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 5.31120 | 0.43620 | 12.18 | <.0001 | 0 |
| Exp | Experience | 1 | -0.04134 | 0.25607 | -0.16 | 0.8720 | -0.01376 |
| CO_TR | Trust | 1 | -0.33208 | 0.08159 | -4.07 | <.0001 | -0.34938 |
| CO_KN | Knowledge | 1 | -0.09857 | 0.06981 | -1.41 | 0.1605 | -0.12476 |
| CO_HB | Habit | 1 | -0.01910 | 0.09088 | -0.21 | 0.8339 | -0.02132 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00764 | 0.00716 | -1.07 | 0.2876 | -0.10783 |
| Z2 | Gender | 1 | 0.02687 | 0.22253 | 0.12 | 0.9041 | 0.01052 |

Individual regressions

Experience -> Perceived risks

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 5.65140 | 1.88380 | 1.22 | 0.3059 |
| **Error** | 124 | 191.70624 | 1.54602 | | |
| **Corrected total** | 127 | 197.35764 | | | |

Trust -> Perceived risks

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 30.45161 | 10.15054 | 7.54 | 0.0001 |
| **Error** | 124 | 166.90602 | 1.34602 | | |

| | | | | | |
|---|---|---|---|---|---|
| **Corrected total** | 127 | 197.35764 | | | |
| **Root MSE** | 1.16018 | **R-square** | 0.1543 | | |
| **Dependent mean** | 3.39063 | **R-square adj.** | 0.1338 | | |
| **Coeff Var** | 34.21727 | | | | |

| **Estimated parameters** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 5.03609 | 0.38048 | 13.24 | <.0001 | 0 |
| CO_TR | Trust | 1 | -0.34909 | 0.07970 | -4.38 | <.0001 | -0.36728 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00992 | 0.00586 | -1.69 | 0.0930 | -0.13994 |
| Z2 | Gender | 1 | -0.04541 | 0.21422 | -0.21 | 0.8325 | -0.01778 |

Knowledge -> Perceived risks

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 10.03058 | 3.34353 | 2.21 | 0.0899 |
| **Error** | 124 | 187.32706 | 1.51070 | | |
| **Corrected total** | 127 | 197.35764 | | | |

Habit -> Perceived risks

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 4.75324 | 1.58441 | 1.02 | 0.3862 |
| **Error** | 124 | 192.60440 | 1.55326 | | |
| **Corrected total** | 127 | 197.35764 | | | |

# Appendix I: Coronalert, Moderation analysis

## Appendix I.1: Transparency

| **Model Summary** | | | | | | |
|---|---|---|---|---|---|---|
| **R** | **R-sq** | **MSE** | **F** | **df1** | **df2** | **p** |
| 0.5411 | 0.2927 | 2.8921 | 17.1083 | 3.0000 | 124.0000 | 0.0000 |
| **Model** | | | | | | |
| | **coeff** | **se** | **t** | **p** | **LLCI** | **ULCI** |
| **constant** | 4.2295 | 1.3156 | 3.2150 | 0.0017 | 1.6257 | 6.8334 |
| **CO_PR** | -0.5952 | 0.3815 | -1.5602 | 0.1213 | -1.3503 | 0.1599 |
| **CO_TRP** | 0.5513 | 0.3179 | 1.7345 | 0.0853 | -0.0778 | 1.1805 |
| **Int_1** | -0.0279 | 0.0965 | -0.2893 | 0.7728 | -0.2190 | 0.1632 |

Since there the moderator is not significant, it is interesting to analyze if transparency has a direct impact on the adoption of the app.

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 57.69849 | 19.23283 | 5.31 | 0.0018 |
| **Error** | 124 | 449.35620 | 3.62384 | | |
| **Corrected total** | 127 | 507.05469 | | | |
| **Root MSE** | 1.90364 | **R-square** | 0.1138 | | |
| **Dependent mean** | 3.83594 | **R-square adj.** | 0.0924 | | |
| **Coeff Var** | 49.62643 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 1.58759 | 0.67472 | 2.35 | 0.0202 | 0 |
| CO_TRP | Transparency regarding Coronalert | 1 | 0.65204 | 0.16521 | 3.95 | 0.0001 | 0.34325 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00566 | 0.00988 | -0.57 | 0.5678 | -0.04980 |
| Z2 | Gender | 1 | 0.23270 | 0.34681 | 0.67 | 0.5035 | 0.05683 |

# Appendix I.2: Control

| Model Summary | | | | | | |
|---|---|---|---|---|---|---|
| **R** | **R-sq** | **MSE** | **F** | **df1** | **df2** | **p** |
| 0.5429 | 0.2947 | 2.8839 | 17.2737 | 3.0000 | 124.0000 | 0.0000 |
| **Model** | | | | | | |
| | **coeff** | **se** | **t** | **p** | **LLCI** | **ULCI** |
| **constant** | 3.3708 | 1.6009 | 2.1056 | 0.0373 | 0.2022 | 6.5394 |
| **CO_PR** | -0.4437 | 0.4118 | -1.0775 | 0.2833 | -1.2588 | 0.3714 |
| **CO_C** | 0.4800 | 0.2927 | 1.6399 | 0.1036 | -0.0993 | 1.0593 |
| **Int_1** | -0.0172 | 0.0843 | -0.2035 | 0.8391 | -0.1841 | 0.1498 |

Since there the moderator is not significant, it is interesting to analyze if control has a direct impact on the adoption of the app.

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 111.38596 | 37.12865 | 11.64 | <.0001 |
| **Error** | 124 | 395.66873 | 3.19088 | | |
| **Corrected total** | 127 | 507.05469 | | | |
| **Root MSE** | 1.78630 | **R-square** | 0.2197 | | |
| **Dependent mean** | 3.83594 | **R-square adj.** | 0.2008 | | |
| **Coeff Var** | 46.56756 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 0.77862 | 0.63367 | 1.23 | 0.2215 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| CO_C | Control over Coronalert | 1 | 0.68648 | 0.11685 | 5.88 | <.0001 | 0.47159 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00328 | 0.00909 | -0.36 | 0.7190 | -0.02884 |
| Z2 | Gender | 1 | -0.00654 | 0.32622 | -0.02 | 0.9840 | -0.00160 |

# Appendix I.3: Bandwagon

| **Model Summary** | | | | | | |
|---|---|---|---|---|---|---|
| **R** | **R-sq** | **MSE** | **F** | **df1** | **df2** | **p** |
| 0.5161 | 0.2663 | 3.0000 | 15.0054 | 3.0000 | 124.0000 | 0.0000 |
| **Model** | | | | | | |
| | **coeff** | **se** | **t** | **p** | **LLCI** | **ULCI** |
| **constant** | 4.5692 | 1.0852 | 4.2106 | 0.0000 | 2.4214 | 6.7171 |
| **CO_PR** | -0.4162 | 0.3008 | -1.3833 | 0.1691 | -1.0116 | 0.1793 |
| **CO_BW** | 0.7417 | 0.3916 | 1.8943 | 0.0605 | -0.0333 | 1.5168 |
| **Int_1** | -0.1394 | 0.1098 | -1.2700 | 0.2065 | -0.3567 | 0.0779 |

Since there the moderator is not significant, it is interesting to analyze if bandwagon has a direct impact on the adoption of the app.

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 18.07487 | 6.02496 | 1.53 | 0.2106 |
| **Error** | 124 | 488.97982 | 3.94339 | | |
| **Corrected total** | 127 | 507.05469 | | | |

# Appendix J: CovidsafeBE, Descriptive statistics

| **Variable** | **Label** | **N** | **Average** | **Std dev** | **Minimum** | **Maximum** |
|---|---|---|---|---|---|---|
| Z2 | Gender | 122 | 0.6147541 | 0.4886602 | 0 | 1.0000000 |
| Age | How old are you? (from 15.5 to 80 year's old) | 122 | 37.4754098 | 17.6064475 | 15.5000000 | 80.0000000 |
| Z5 | Student | 122 | 0.3688525 | 0.4844835 | 0 | 1.0000000 |
| Z6 | Employee | 122 | 0.2295082 | 0.4222507 | 0 | 1.0000000 |
| Z7 | Retired | 122 | 0.0737705 | 0.2624750 | 0 | 1.0000000 |
| Z8 | Civil servent | 122 | 0.1393443 | 0.3477335 | 0 | 1.0000000 |
| Z9 | Long-term illness | 122 | 0.0081967 | 0.0905357 | 0 | 1.0000000 |
| Z10 | Self-employed | 122 | 0.0737705 | 0.2624750 | 0 | 1.0000000 |
| Z11 | Manager | 122 | 0.0327869 | 0.1788127 | 0 | 1.0000000 |
| Z12 | Currently unemployed | 122 | 0.0327869 | 0.1788127 | 0 | 1.0000000 |
| Z13 | Disability | 122 | 0.0245902 | 0.1555111 | 0 | 1.0000000 |
| Z14 | Liberal proffesion | 122 | 0.0163934 | 0.1275067 | 0 | 1.0000000 |
| Z15 | Higher secondary | 122 | 0.1803279 | 0.3860457 | 0 | 1.0000000 |
| Z16 | Bachelor | 122 | 0.3196721 | 0.4682726 | 0 | 1.0000000 |
| Z17 | Master | 122 | 0.4918033 | 0.5019944 | 0 | 1.0000000 |
| Z18 | PhD | 122 | 0.0081967 | 0.0905357 | 0 | 1.0000000 |
| BE | CovidsafeBE | 122 | 1.0000000 | 0 | 1.0000000 | 1.0000000 |

# Appendix K: CovidsafeBE, Measurement scale analysis

## Appendix K.1: Trust construct

4 items

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| TR2 | TR_true_statement | 0.91480 |
| TR3 | TR_honest | 0.90766 |
| TR1 | TR_trust | 0.87755 |
| TR4i | TR_disbelief | 0.67178 |

| Final Communality Estimates: Total = 2.882078 | | | |
|---|---|---|---|
| TR1 | TR2 | TR3 | TR4i |
| 0.77008576 | 0.83685061 | 0.82385526 | 0.45128649 |

EFA without TR4i:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| TR2 | TR_true_statement | 0.91481 |
| TR3 | TR_honest | 0.90587 |
| TR1 | TR_trust | 0.87331 |

| Final Communality Estimates: Total = 2.420158 | | |
|---|---|---|
| TR1 | TR2 | TR3 |
| 0.76267125 | 0.83688318 | 0.82060361 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |
| Raw | 0.936349 |
| Standardized | 0.936379 |

## Appendix K.2: Knowledge construct

6 items

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| KN6 | KN_ease_use | 0.92907 |
| KN2 | KN_use | 0.91917 |
| KN5 | KN_concepts | 0.89551 |
| KN3 | KN_define | 0.89520 |
| KN1 | KN_explain | 0.89041 |
| KN4 | KN_basic | 0.86267 |

| Final Communality Estimates: Total = 4.848393 | | | | | |
|---|---|---|---|---|---|
| KN1 | KN2 | KN3 | KN4 | KN5 | KN6 |
| 0.79282747 | 0.84486818 | 0.80138367 | 0.74420014 | 0.80194694 | 0.86316628 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| **Variables** | **Alpha** |
| Raw | 0.961169 |
| Standardized | 0.961373 |

**Bandwagon construct**

3 items

EFA:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| BW3 | BW_recognised | 0.87620 |
| BW2 | BW_approved | 0.85074 |
| BW1 | BW_used | 0.83679 |
| **Final Communality Estimates: Total = 2.191711** | | |
| **BW1** | **BW2** | **BW3** |
| 0.70022145 | 0.72375957 | 0.76773039 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| **Variables** | **Alpha** |
| Raw | 0.905924 |
| Standardized | 0.906374 |

# Appendix K.3: Habit construct

12 items

EFA:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| HB5 | HB_thinking | 0.86128 |
| HB10 | HB_no_thinking | 0.81927 |
| HB2 | HB_automatic | 0.81387 |
| HB3 | HB_remember | 0.79530 |
| HB8 | HB_realize | 0.78856 |
| HB7 | HB_routine | 0.76867 |
| HB9 | HB_hard | 0.76733 |
| HB12 | HB_long_time | 0.74468 |
| HB1 | HB_often | 0.73361 |
| HB6 | HB_effort | 0.70184 |
| HB4 | HB_sensation | 0.61958 |
| HB11 | HB_typically_me | 0.58848 |

| Final Communality Estimates: Total = 6.824876 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **HB1** | **HB2** | **HB3** | **HB4** | **HB6** | **HB5** | **HB7** | **HB8** | **HB9** | **HB10** | **HB11** | **HB12** |
| 0.5381 7826 | 0.66238 995 | 0.6325 0673 | 0.3838 8306 | 0.4925 8230 | 0.7418 0170 | 0.5908 5148 | 0.6218 3231 | 0.5888 0137 | 0.6712 0039 | 0.3463 0482 | 0.5545 4324 |

EFA without HB4, HB6 and HB11:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| HB5 | HB_thinking | 0.85489 |
| HB2 | HB_automatic | 0.85430 |
| HB10 | HB_no_thinking | 0.81044 |
| HB3 | HB_remember | 0.80526 |

| | | |
|---|---|---|
| HB7 | HB_routine | 0.79898 |
| HB1 | HB_often | 0.78667 |
| HB12 | HB_long_time | 0.77514 |
| HB8 | HB_realize | 0.76073 |
| HB9 | HB_hard | 0.68490 |

| Final Communality Estimates: Total = 5.671781 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **HB1** | **HB2** | **HB3** | **HB5** | **HB7** | **HB8** | **HB9** | **HB10** | **HB12** |
| 0.61884466 | 0.72983657 | 0.64844782 | 0.73083754 | 0.63837055 | 0.57870579 | 0.46908230 | 0.65680911 | 0.60084618 |

EFA without HB9:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| HB2 | HB_automatic | 0.86563 |
| HB5 | HB_thinking | 0.84454 |
| HB7 | HB_routine | 0.81209 |
| HB3 | HB_remember | 0.80894 |
| HB1 | HB_often | 0.80884 |
| HB10 | HB_no_thinking | 0.78533 |
| HB12 | HB_long_time | 0.78278 |
| HB8 | HB_realize | 0.73482 |

| Final Communality Estimates: Total = 5.200110 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **HB1** | **HB2** | **HB3** | **HB5** | **HB7** | **HB8** | **HB10** | **HB12** |
| 0.65422059 | 0.74931573 | 0.65437693 | 0.71325565 | 0.65949449 | 0.53996040 | 0.61674761 | 0.61273890 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| **Variables** | **Alpha** |
| Raw | 0.932271 |
| Standardized | 0.934800 |

# Appendix K.4: Control construct

EFA:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| BE_C2 | BE_C_released | 0.93489 |
| BE_C1 | BE_C_persons | 0.91040 |
| BE_C3 | BE_C_used | 0.90697 |

| Final Communality Estimates: Total = 2.525444 | | |
|---|---|---|
| **BE_C1** | **BE_C2** | **BE_C3** |
| 0.82882468 | 0.87402788 | 0.82259173 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| **Variables** | **Alpha** |
| Raw | 0.949127 |
| Standardized | 0.949304 |

# Appendix K.5: Transparency construct

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| BE_TRP3 | BE_TRP_decisions | 0.87703 |
| BE_TRP2 | BE_TRP_info_rules | 0.83292 |
| BE_TRP4 | BE_TRP_performance | 0.81371 |
| BE_TRP5 | BE_TRP_globally | 0.63060 |
| BE_TRP1 | BE_TRP_activities | 0.48792 |

| Final Communality Estimates: Total = 2.760788 | | | | |
|---|---|---|---|---|
| BE_TRP1 | BE_TRP2 | BE_TRP3 | BE_TRP4 | BE_TRP5 |
| 0.23806975 | 0.69376064 | 0.76917838 | 0.66211813 | 0.39766132 |

EFA without BE_TRP1 and BE_TRP5:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| BE_TRP3 | BE_TRP_decisions | 0.88975 |
| BE_TRP2 | BE_TRP_info_rules | 0.81473 |
| BE_TRP4 | BE_TRP_performance | 0.78991 |

| Final Communality Estimates: Total = 2.079411 | | |
|---|---|---|
| BE_TRP2 | BE_TRP3 | BE_TRP4 |
| 0.66379033 | 0.79165594 | 0.62396439 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |
| Raw | 0.886091 |
| Standardized | 0.886508 |

# Appendix K.6: Perceived benefits construct

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| BE_PB_4 | BE_PB_forget | 0.79379 |
| BE_PB_2 | BE_PB_travel | 0.78717 |
| BE_PB_3 | BE_PB_at_hand | 0.77758 |
| BE_PB_1 | BE_PB_certificate | 0.76672 |

| Final Communality Estimates: Total = 2.442231 | | | |
|---|---|---|---|
| BE_PB_1 | BE_PB_2 | BE_PB_3 | BE_PB_4 |
| 0.58786218 | 0.61963132 | 0.60463669 | 0.63010128 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| Variables | Alpha |
| Raw | 0.873378 |
| Standardized | 0.874246 |

# Appendix K.7: Perceived risks construct

EFA:

| Factor pattern | | |
|---|---|---|
| | | Factor1 |
| BE_PR2 | BE_PR_loss | 0.88208 |
| BE_PR1 | BE_PR_control | 0.84306 |
| BE_PR3 | BE_PR_steal | 0.73098 |

| Final Communality Estimates: Total = 2.023152 | | |
|---|---|---|
| BE_PR1 | BE_PR2 | BE_PR3 |

| | | |
|---|---|---|
| 0.71075572 | 0.77806434 | 0.53433155 |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| **Variables** | **Alpha** |
| Raw | 0.875584 |
| Standardized | 0.875512 |

## Appendix K.8: Adoption construct

EFA:

| Factor pattern | | |
|---|---|---|
| | | **Factor1** |
| BE_AD2 | BE_AD_predict | 0.96457 |
| BE_AD1 | BE_AD_intend | 0.96457 |
| **Final Communality Estimates: Total = 1.860781** | | |
| **BE_AD1** | **BE_AD2** | |
| 0.93039053 | 0.93039053 | |

Cronbach's Alpha:

| Cronbach Coefficient Alpha | |
|---|---|
| **Variables** | **Alpha** |
| Raw | 0.975601 |
| Standardized | 0.975857 |

# Appendix L: CovidsafeBE, Analysis of variance

## Appendix L.1: Immediate benefits

Perceived benefits

ANOVA

| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
|---|---|---|---|---|---|
| Model | 2 | 39.1659372 | 19.5829686 | 15.44 | <.0001 |
| Error | 119 | 150.9616243 | 1.2685851 | | |
| Corrected total | 121 | 190.1275615 | | | |

| **Level of CO_IB** | **N** | **CO_PB** | |
|---|---|---|---|
| | | **Average** | **Std dev** |
| 1 | 11 | 4.00000000 | 1.36930639 |
| 2 | 7 | 2.28571429 | 1.39514464 |
| 3 | 104 | 2.01682692 | 1.08176884 |

Tukey

| | |
|---|---|
| **Alpha** | 0.05 |
| **Degree of freedom de l'Error** | 119 |
| **Error quadratique Average** | 1.268585 |
| **Critical value of studentized range** | 3.35649 |

| **Significant comparisons at the 0.05 level indicated by ***.** | | | | |
|---|---|---|---|---|
| **BE_IB Comparison** | **Difference/between/average** | **Simultaneous 95% - Confidence interval** | | |
| 1-2 | 1.7143 | 0.4218 | 3.0068 | *** |
| 1-3 | 1.9832 | 1.1356 | 2.8307 | *** |

| | | | | |
|---|---|---|---|---|
| 2-3 | 0.2689 | -0.7749 | 1.3127 | |

Perceived risks

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 2 | 30.7582648 | 15.3791324 | 8.65 | 0.0003 |
| Error | 119 | 211.6864073 | 1.7788774 | | |
| Corrected total | 121 | 242.4446721 | | | |

| Level of CO_IB | N | CO_PB | |
|---|---|---|---|
| | | Average | Std dev |
| 1 | 11 | 2.57575758 | 1.49138943 |
| 2 | 7 | 3.04761905 | 1.48359637 |
| 3 | 104 | 3.94230769 | 1.22138647 |

Tukey

| | |
|---|---|
| Alpha | 0.05 |
| Degree of freedom de l'Error | 119 |
| Error quadratique Average | 1.778877 |
| Critical value of studentized range | 3.35649 |

| Significant comparisons at the 0.05 level indicated by ***. | | | | |
|---|---|---|---|---|
| BE_IB Comparison | Difference/between/average | Simultaneous 95% - Confidence interval | | |
| 3-2 | 1.0529 | -0.1832 | 2.2889 | |
| 3-1 | 1.5983 | 0.5947 | 2.6020 | *** |
| 2-1 | 0.5455 | -0.9850 | 2.0760 | |

# Appendix L.2: Gender

Adoption

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 1 | 0.7462440 | 0.7462440 | 0.27 | 0.6052 |
| Error | 120 | 333.2721986 | 2.7772683 | | |
| Corrected total | 121 | 334.0184426 | | | |

Perceived benefits

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 1 | 1.5397955 | 1.5397955 | 0.98 | 0.3242 |
| Error | 120 | 188.5877660 | 1.5715647 | | |
| Corrected total | 121 | 190.1275615 | | | |

Perceived risks

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 1 | 0.0439629 | 0.0439629 | 0.02 | 0.8830 |
| Error | 120 | 242.4007092 | 2.0200059 | | |
| Corrected total | 121 | 242.4446721 | | | |

# Appendix L.3: Age

Adoption

Pearson correlation

| Pearson correlation coefficients, N = 128<br>Prob > \|r\| under H0: Rho=0 | | |
|---|---|---|
| | Age | CO_AD |
| Age<br>How old are you? (from 15.5 to 80 year's old) | 1.00000 | 0.16205<br>0.0745 |
| BE_AD<br>Adoption of the CovidsafeBE application | 0.16205<br>0.0745 | 1.00000 |

Perceived benefits

| Pearson correlation coefficients, N = 128<br>Prob > \|r\| under H0: Rho=0 | | |
|---|---|---|
| | Age | CO_AD |
| Age<br>How old are you? (from 15.5 to 80 year's old) | 1.00000 | 0.25146<br>0.0052 |
| BE_AD<br>Adoption of the CovidsafeBE application | 0.25146<br>0.0052 | 1.00000 |

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 7 | 31.8510511 | 4.5501502 | 3.28 | 0.0033 |
| Error | 114 | 158.2765104 | 1.3883904 | | |
| Corrected total | 121 | 190.1275615 | | | |

| Level of CO_IB | N | CO_PB Average | CO_PB Std dev |
|---|---|---|---|
| 0 | 1 | 1.00000000 | . |
| 1 | 50 | 1.94000000 | 1.07209503 |
| 2 | 16 | 2.39062500 | 1.04868469 |
| 3 | 5 | 1.85000000 | 1.51657509 |
| 4 | 8 | 2.50000000 | 1.21007674 |
| 5 | 28 | 2.12500000 | 1.33420111 |
| 6 | 12 | 2.83333333 | 1.22164817 |
| 7 | 2 | 5.37500000 | 1.23743687 |

| Alpha | 0.05 |
|---|---|
| Degree of freedom de l'Error | 114 |

| | |
|---|---|
| **Error quadratique Average** | 1.38839 |
| **Critical value of studentized range** | 4.36705 |

| **Significant comparisons at the 0.05 level indicated by ***.** | | | | |
|---|---|---|---|---|
| **CO_IB Comparison** | **Difference/between/average** | **Simultaneous 95% - Confidence interval** | | |
| 7 - 6 | 2.5417 | -0.2373 | 5.3207 | |
| 7 - 4 | 2.8750 | -0.0015 | 5.7515 | |
| 7 - 2 | 2.9844 | 0.2555 | 5.7133 | *** |
| 7 - 5 | 3.2500 | 0.5869 | 5.9131 | *** |
| 7 - 1 | 3.4350 | 0.8112 | 6.0588 | *** |
| 7 - 3 | 3.5250 | 0.4808 | 6.5692 | *** |
| 7 - 0 | 4.3750 | -0.0813 | 8.8313 | |
| 6 - 4 | 0.3333 | -1.3274 | 1.9941 | |
| 6 - 2 | 0.4427 | -0.9468 | 1.8322 | |
| 6 - 5 | 0.7083 | -0.5471 | 1.9638 | |
| 6 - 1 | 0.8933 | -0.2763 | 2.0630 | |
| 6 - 3 | 0.9833 | -0.9534 | 2.9201 | |
| 6 - 0 | 1.8333 | -1.9538 | 5.6205 | |
| 4 - 2 | 0.1094 | -1.4662 | 1.6849 | |
| 4 - 5 | 0.3750 | -1.0837 | 1.8337 | |
| 4 - 1 | 0.5600 | -0.8255 | 1.9455 | |
| 4 - 3 | 0.6500 | -1.4243 | 2.7243 | |
| 4 - 0 | 1.5000 | -2.3593 | 5.3593 | |
| 2 - 5 | 0.2656 | -0.8747 | 1.4059 | |
| 2 - 1 | 0.4506 | -0.5945 | 1.4957 | |
| 2 - 3 | 0.5406 | -1.3236 | 2.4048 | |
| 2 - 0 | 1.3906 | -2.3599 | 5.1412 | |
| 5 - 1 | 0.1850 | -0.6738 | 1.0438 | |
| 5 - 3 | 0.2750 | -1.4915 | 2.0415 | |
| 5 - 0 | 1.1250 | -2.5780 | 4.8280 | |
| 1 - 3 | 0.0900 | -1.6166 | 1.7966 | |
| 1 - 0 | 0.9400 | -2.7348 | 4.6148 | |
| 3 - 0 | 0.8500 | -3.1358 | 4.8358 | |

Perceived risks

| **Pearson correlation coefficients, N = 128**<br>**Prob > \|r\| under H0: Rho=0** | | |
|---|---|---|
| | **Age** | **CO_AD** |
| **Age**<br>**How old are you? (from 15.5 to 80 year's old)** | 1.00000 | -0.17466<br>0.0543 |
| **BE_AD**<br>**Adoption of the CovidsafeBE application** | -0.17466<br>0.0543 | 1.00000 |

# Appendix L.4: Education

Adoption

Anova

| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
|---|---|---|---|---|---|
| Model | 3 | 33.8365370 | 11.2788457 | 4.43 | 0.0054 |
| Error | 118 | 300.1819056 | 2.5439145 | | |
| Corrected total | 121 | 334.0184426 | | | |

| Level of CO_IB | N | CO_PB | |
|---|---|---|---|
| | | Average | Std dev |
| 0 | 22 | 2.02272727 | 1.05195139 |
| 1 | 39 | 2.78205128 | 1.97948316 |
| 2 | 60 | 2.14166667 | 1.47318307 |
| 3 | 1 | 7.00000000 | . |

Tukey

| | |
|---|---|
| Alpha | 0.05 |
| Degree of freedom de l'Error | 118 |
| Error quadratique Average | 2.543914 |
| Critical value of studentized range | 3.68547 |

| Significant comparisons at the 0.05 level indicated by ***. | | | | |
|---|---|---|---|---|
| Z3 Comparison | Difference/between/average | Simultaneous 95% - Confidence interval | | |
| 3 - 1 | 4.2179 | 0.0085 | 8.4274 | *** |
| 3 - 2 | 4.8583 | 0.6673 | 9.0493 | *** |
| 3 - 0 | 4.9773 | 0.7273 | 9.2272 | *** |
| 1 - 2 | 0.6404 | -0.2146 | 1.4953 | |
| 1 - 0 | 0.7593 | -0.3490 | 1.8676 | |

Perceived benefits

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 3 | 9.8932739 | 3.2977580 | 2.16 | 0.0965 |
| Error | 118 | 180.2342876 | 1.5274092 | | |
| Corrected total | 121 | 190.1275615 | | | |

Perceived risks

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 3 | 13.0613073 | 4.3537691 | 2.59 | 0.0562 |
| Error | 118 | 198.4696581 | 1.6819463 | | |
| Corrected total | 121 | 211.5309654 | | | |

# Appendix L.5: Occupation

Adoption

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 9 | 38.6924039 | 4.2991560 | 1.63 | 0.1150 |
| Error | 112 | 295.3260387 | 2.6368396 | | |
| Corrected total | 121 | 334.0184426 | | | |

Perceived benefits

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 9 | 43.2527482 | 4.8058609 | 3.66 | 0.0005 |
| Error | 112 | 146.8748133 | 1.3113823 | | |
| Corrected total | 121 | 190.1275615 | | | |

| Level of CO_IB | N | CO_PB | |
|---|---|---|---|
| | | Average | Std dev |
| 0 | 45 | 1.98333333 | 1.10833618 |
| 1 | 28 | 1.89285714 | 1.01477185 |
| 2 | 9 | 3.55555556 | 1.63830027 |
| 3 | 17 | 1.85294118 | 0.77590080 |
| 4 | 1 | 1.00000000 | . |
| 5 | 9 | 2.66666667 | 1.14564392 |
| 6 | 4 | 2.50000000 | 1.41421356 |
| 7 | 4 | 4.00000000 | 2.16024690 |
| 8 | 3 | 3.16666667 | 1.28290036 |
| 9 | 2 | 1.75000000 | 0.35355339 |

Tukey

| | |
|---|---|
| Alpha | 0.05 |
| Degree of freedom de l'Error | 112 |
| Error quadratique Average | 1.311382 |
| Critical value of studentized range | 4.56569 |

| Significant comparisons at the 0.05 level indicated by ***. | | | | |
|---|---|---|---|---|
| Z4 Comparison | Difference/between/average | Simultaneous 95% - Confidence interval | | |
| 7 - 2 | 0.4444 | -1.7772 | 2.6661 | |
| 7 - 8 | 0.8333 | -1.9903 | 3.6570 | |
| 7 - 5 | 1.3333 | -0.8883 | 3.5550 | |
| 7 - 6 | 1.5000 | -1.1142 | 4.1142 | |
| 7 - 0 | 2.0167 | 0.0877 | 3.9456 | *** |
| 7 - 1 | 2.1071 | 0.1310 | 4.0833 | *** |
| 7 - 3 | 2.1471 | 0.0925 | 4.2016 | *** |
| 7 - 9 | 2.2500 | -0.9517 | 5.4517 | |
| 7 - 4 | 3.0000 | -1.1334 | 7.1334 | |
| 2 - 8 | 0.3889 | -2.0758 | 2.8536 | |
| 2 - 5 | 0.8889 | -0.8539 | 2.6317 | |
| 2 - 6 | 1.0556 | -1.1661 | 3.2772 | |
| 2 - 0 | 1.5722 | 0.2222 | 2.9222 | *** |
| 2 - 1 | 1.6627 | 0.2461 | 3.0793 | *** |
| 2 - 3 | 1.7026 | 0.1786 | 3.2267 | *** |
| 2 - 4 | 2.5556 | -1.3415 | 6.4526 | |
| 8 - 5 | 0.5000 | -1.9647 | 2.9647 | |
| 8 - 6 | 0.6667 | -2.1570 | 3.4903 | |
| 8 - 0 | 1.1833 | -1.0212 | 3.3878 | |
| 8 - 1 | 1.2738 | -0.9721 | 3.5197 | |
| 8 - 3 | 1.3137 | -1.0015 | 3.6289 | |
| 8 - 9 | 1.4167 | -1.9583 | 4.7916 | |
| 8 - 4 | 2.1667 | -2.1023 | 6.4357 | |
| 5 - 6 | 0.1667 | -2.0550 | 2.3883 | |
| 5 - 0 | 0.6833 | -0.6666 | 2.0333 | |

| | | | | |
|---|---|---|---|---|
| 5 - 1 | 0.7738 | -0.6428 | 2.1904 | |
| 5 - 3 | 0.8137 | -0.7103 | 2.3378 | |
| 5 - 9 | 0.9167 | -1.9735 | 3.8068 | |
| 5 - 4 | 1.6667 | -2.2304 | 5.5637 | |
| 6 - 0 | 0.5167 | -1.4123 | 2.4456 | |
| 6 - 1 | 0.6071 | -1.3690 | 2.5833 | |
| 6 - 3 | 0.6471 | -1.4075 | 2.7016 | |
| 6 - 9 | 0.7500 | -2.4517 | 3.9517 | |
| 6 - 4 | 1.5000 | -2.6334 | 5.6334 | |
| 0 - 1 | 0.0905 | -0.7994 | 0.9804 | |
| 0 - 3 | 0.1304 | -0.9221 | 1.1829 | |
| 0 - 9 | 0.2333 | -2.4383 | 2.9050 | |
| 0 - 4 | 0.9833 | -2.7546 | 4.7212 | |
| 1 - 3 | 0.0399 | -1.0968 | 1.1767 | |
| 1 - 9 | 0.1429 | -2.5631 | 2.8488 | |
| 1 - 4 | 0.8929 | -2.8696 | 4.6554 | |
| 3 - 9 | 0.1029 | -2.6608 | 2.8667 | |
| 3 - 4 | 0.8529 | -2.9513 | 4.6572 | |
| 9 - 4 | 0.7500 | -3.7780 | 5.2780 | |

Perceived risks

Anova

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| Model | 9 | 28.0272001 | 3.1141333 | 1.63 | 0.1160 |
| Error | 112 | 214.4174720 | 1.9144417 | | |
| Corrected total | 121 | 242.4446721 | | | |

# Appendix M: CovidsafeBE, Descriptive statistics and correlation

| Variable | Label | Average | Std dev | Minimum | Maximum |
|---|---|---|---|---|---|
| Exp | Experience | 0.2131148 | 0.4111968 | 0 | 1 |
| BE_TR | Trust | 3.5546448 | 1.2666599 | 1 | 7 |
| BE_HB | Habit | 3.0276639 | 1.3860387 | 1 | 7 |
| BE_BW | Bandwagon | 2.5300546 | 1.1263226 | 1 | 7 |
| BE_KN | Knowledge | 3.9972678 | 1.5856310 | 1 | 7 |
| IB_Cat1 | Respondents who would never download CovidsafeBE | 0.0901639 | 0.2875976 | 0 | 1 |
| IB_Cat2 | Respondents who would download CovidsafeBE if the benefits were noticeable in one month or less | 0.0573770 | 0.2335207 | 0 | 1 |
| IB_Cat3 | Respondents who would download CovidsafeBE even if benefits are on the long term | 0.8524590 | 0.3561068 | 0 | 1 |
| BE_C | Control over CovidsafeBE | 4.3360656 | 1.3205280 | 1 | 7 |
| BE_TRP | Transparancy over CovidsafeBE | 3.6939891 | 1.0405817 | 1 | 7 |
| BE_PR | Perceived risks regarding data privacy on CovidsafeBE | 3.7677596 | 1.3221913 | 1 | 7 |
| BE_PB | Perceived benefits of CovidsafeBE | 2.2110656 | 1.2535159 | 1 | 7 |
| BE_AD | Adoption of CovidsafeBE | 2.3647541 | 1.6614701 | 1 | 7 |

| | | | | | |
|---|---|---|---|---|---|
| Age | How old are you? (from 15.5 to 80 year's old) | 37.4754098 | 17.6064475 | 15.50 | 80 |
| Z2 | Gender | 0.6147541 | 0.4886602 | 0 | 1 |
| Z5 | Student | 0.3688525 | 0.4844835 | 0 | 1 |
| Z6 | Employee | 0.2295082 | 0.4222507 | 0 | 1 |
| Z7 | Retired | 0.0737705 | 0.2624750 | 0 | 1 |
| Z8 | Civil servent | 0.1393443 | 0.3477335 | 0 | 1 |
| Z9 | Long-term illness | 0.0081967 | 0.0905357 | 0 | 1 |
| Z10 | Self-employed | 0.0737705 | 0.2624750 | 0 | 1 |
| Z11 | Manager | 0.0327869 | 0.1788127 | 0 | 1 |
| Z12 | Currently unemployed | 0.0327869 | 0.1788127 | 0 | 1 |
| Z14 | Liberal proffesion | 0.0163934 | 0.1275067 | 0 | 1 |
| Z15 | Higher secondary | 0.1803279 | 0.3860457 | 0 | 1 |
| Z16 | Bachelor | 0.3196721 | 0.4682726 | 0 | 1 |
| Z17 | Master | 0.4918033 | 0.5019944 | 0 | 1 |
| Z18 | PhD | 0.0081967 | 0.0905357 | 0 | 1 |

**Coefficients de corrélation de Pearson, N = 122**
**Proba > |r| sous H0: Rho=0**

| | Exp | BE_TR | BE_HB | BE_KN | BE_PR | BE_PB | BE_AD | Age | Z2 |
|---|---|---|---|---|---|---|---|---|---|
| **Exp Experience** | 1.00000 | -0.14142<br>0.1202 | -0.16269<br>0.0734 | 0.02625<br>0.7741 | -0.17676<br>0.0515 | -0.06394<br>0.4841 | -0.09053<br>0.3214 | -0.10658<br>0.2427 | -0.08159<br>0.3717 |
| **BE_TR Trust** | -0.14142<br>0.1202 | 1.00000 | -0.00077<br>0.9933 | 0.20445<br>0.0239 | -0.44717<br><.0001 | 0.23840<br>0.0082 | 0.31410<br>0.0004 | 0.00784<br>0.9317 | 0.16559<br>0.0683 |
| **BE_HB Habit** | -0.16269<br>0.0734 | -0.00077<br>0.9933 | 1.00000 | 0.15970<br>0.0789 | -0.09060<br>0.3210 | 0.29762<br>0.0009 | 0.28246<br>0.0016 | 0.60071<br><.0001 | 0.00824<br>0.9282 |
| **BE_KN Knowledge** | 0.02625<br>0.7741 | 0.20445<br>0.0239 | 0.15970<br>0.0789 | 1.00000 | -0.23267<br>0.0099 | 0.16263<br>0.0735 | 0.09841<br>0.2808 | 0.18201<br>0.0448 | 0.26528<br>0.0031 |
| **BE_PR Perceived risks regarding data privacy on CovidsafeBE** | -0.17676<br>0.0515 | -0.44717<br><.0001 | -0.09060<br>0.3210 | -0.23267<br>0.0099 | 1.00000 | -0.20122<br>0.0263 | -0.32353<br>0.0003 | -0.18687<br>0.0393 | 0.02240<br>0.8065 |
| **BE_PB Perceived benefits of CovidsafeBE** | -0.06394<br>0.4841 | 0.23840<br>0.0082 | 0.29762<br>0.0009 | 0.16263<br>0.0735 | -0.20122<br>0.0263 | 1.00000 | 0.70825<br><.0001 | 0.25146<br>0.0052 | 0.08999<br>0.3242 |
| **BE_AD Adoption of CovidsafeBE** | -0.09053<br>0.3214 | 0.31410<br>0.0004 | 0.28246<br>0.0016 | 0.09841<br>0.2808 | -0.32353<br>0.0003 | 0.70825<br><.0001 | 1.00000 | 0.16205<br>0.0745 | 0.04727<br>0.6052 |
| **Age How old are you? (from 15.5 to 80 year's old)** | -0.10658<br>0.2427 | 0.00784<br>0.9317 | 0.60071<br><.0001 | 0.18201<br>0.0448 | -0.18687<br>0.0393 | 0.25146<br>0.0052 | 0.16205<br>0.0745 | 1.00000 | 0.05652<br>0.5363 |
| **Z2 Gender** | -0.08159<br>0.3717 | 0.16559<br>0.0683 | 0.00824<br>0.9282 | 0.26528<br>0.0031 | 0.02240<br>0.8065 | 0.08999<br>0.3242 | 0.04727<br>0.6052 | 0.05652<br>0.5363 | 1.00000 |

# Appendix N: CovidsafeBE, Multicollinearity test

Adoption: Variance Inflation Factor and Tolerance

**Parameter estimates**

| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Tolerance | Variance inflation |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Intercept** | Intercept | 1 | 1.46569 | 0.47362 | 3.09 | 0.0025 | . | 0 |
| **BE_PR** | Perceived risks regarding data privacy on CovidsafeBE | 1 | -0.24476 | 0.08157 | -3.00 | 0.0033 | 0.93760 | 1.06655 |
| **BE_PB** | Perceived benefits of CovidsafeBE | 1 | 0.90272 | 0.08755 | 10.31 | <.0001 | 0.90552 | 1.10433 |
| **Age** | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00427 | 0.00620 | -0.69 | 0.4927 | 0.91583 | 1.09191 |
| **Z2** | Gender | 1 | -0.02416 | 0.21496 | -0.11 | 0.9107 | 0.98848 | 1.01166 |

| **Collinearity diagnostic** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Proportion of variation** | | | | | |
| **Number** | **Eigenvalue** | **Condition index** | **Intercept** | **BE_PR** | **BE_PB** | **Age** | **Z2** |
| **1** | 4.26529 | 1.00000 | 0.00253 | 0.00491 | 0.01003 | 0.00788 | 0.01527 |
| **2** | 0.33046 | 3.59266 | 0.00285 | 0.00316 | 0.06042 | 0.03803 | 0.92490 |
| **3** | 0.22127 | 4.39046 | 0.01302 | 0.20923 | 0.43899 | 0.01436 | 0.04043 |
| **4** | 0.14887 | 5.35276 | 0.00089182 | 0.06172 | 0.36829 | 0.72396 | 0.00388 |
| **5** | 0.03412 | 11.18145 | 0.98070 | 0.72098 | 0.12228 | 0.21578 | 0.01552 |

Perceived benefits: Variance Inflation Factor and Tolerance

| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Tolerance** | **Variance inflation** |
|---|---|---|---|---|---|---|---|---|
| **Intercept** | Intercept | 1 | 0.34708 | 0.44742 | 0.78 | 0.4395 | . | 0 |
| **BE_TR** | Trust | 1 | 0.22650 | 0.08804 | 2.57 | 0.0114 | 0.92293 | 1.08351 |
| **BE_HB** | Habit | 1 | 0.19917 | 0.09787 | 2.04 | 0.0441 | 0.62366 | 1.60344 |
| **BE_KN** | Knowledge | 1 | 0.04501 | 0.07254 | 0.62 | 0.5362 | 0.86747 | 1.15278 |
| **Exp** | Experience | 1 | -0.14998 | 0.26875 | -0.56 | 0.5779 | 0.93980 | 1.06406 |
| **Age** | How old are you? (from 15.5 to 80 year's old) | 1 | 0.00714 | 0.00766 | 0.93 | 0.3533 | 0.63042 | 1.58624 |
| **Z2** | Gender | 1 | 0.06539 | 0.23084 | 0.28 | 0.7775 | 0.90195 | 1.10871 |

| **Collinearity diagnostic** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Proportion of variation** | | | | | | | |
| **Number** | **Eigenvalue** | **Condition index** | **Intercept** | **BE_TR** | **BE_HB** | **BE_KN** | **Exp** | **Age** | **Z2** |
| **1** | 5.48474 | 1.00000 | 0.00180 | 0.00312 | 0.00311 | 0.00355 | 0.00635 | 0.00330 | 0.00814 |
| **2** | 0.79717 | 2.62302 | 0.00008301 | 0.00001528 | 0.00333 | 0.00040323 | 0.85743 | 0.00261 | 0.01246 |
| **3** | 0.34791 | 3.97051 | 0.00142 | 0.00000192 | 0.04288 | 0.00008509 | 0.00331 | 0.03753 | 0.73423 |
| **4** | 0.15998 | 5.85516 | 0.02185 | 0.21804 | 0.09177 | 0.08899 | 0.11928 | 0.15223 | 0.22010 |
| **5** | 0.09704 | 7.51815 | 0.00818 | 0.31732 | 0.00779 | 0.81443 | 0.00236 | 0.00046946 | 0.01842 |
| **6** | 0.06960 | 8.87690 | 0.00123 | 0.01344 | 0.77397 | 5.425009E-8 | 0.00732 | 0.78980 | 0.00626 |
| **7** | 0.04356 | 11.22150 | 0.96543 | 0.44806 | 0.07715 | 0.09255 | 0.00394 | 0.01405 | 0.00039824 |

Perceived risks: Variance Inflation Factor and Tolerance

| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Tolerance** | **Variance inflation** |
|---|---|---|---|---|---|---|---|---|
| **Intercept** | Intercept | 1 | 6.14522 | 0.43691 | 14.07 | <.0001 | . | 0 |
| **BE_TR** | Trust | 1 | -0.43896 | 0.08597 | -5.11 | <.0001 | 0.92293 | 1.08351 |
| **BE_HB** | Habit | 1 | 0.02761 | 0.09557 | 0.29 | 0.7732 | 0.62366 | 1.60344 |
| **BE_KN** | Knowledge | 1 | -0.12339 | 0.07084 | -1.74 | 0.0842 | 0.86747 | 1.15278 |
| **Exp** | Experience | 1 | -0.38133 | 0.26244 | -1.45 | 0.1489 | 0.93980 | 1.06406 |
| **Age** | How old are you? (from 15.5 to 80 year's old) | 1 | -0.01458 | 0.00748 | -1.95 | 0.0538 | 0.63042 | 1.58624 |
| **Z2** | Gender | 1 | 0.35811 | 0.22542 | 1.59 | 0.1149 | 0.90195 | 1.10871 |

| **Collinearity diagnostic** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Proportion of variation** | | | | | | | |
| **Number** | **Eigenvalue** | **Condition index** | **Intercept** | **BE_TR** | **BE_HB** | **BE_KN** | **Exp** | **Age** | **Z2** |
| **1** | 5.48474 | 1.00000 | 0.00180 | 0.00312 | 0.00311 | 0.00355 | 0.00635 | 0.00330 | 0.00814 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **2** | 0.79717 | 2.62302 | 0.00008301 | 0.00001528 | 0.00333 | 0.00040323 | 0.85743 | 0.00261 | 0.01246 |
| **3** | 0.34791 | 3.97051 | 0.00142 | 0.00000192 | 0.04288 | 0.00008509 | 0.00331 | 0.03753 | 0.73423 |
| **4** | 0.15998 | 5.85516 | 0.02185 | 0.21804 | 0.09177 | 0.08899 | 0.11928 | 0.15223 | 0.22010 |
| **5** | 0.09704 | 7.51815 | 0.00818 | 0.31732 | 0.00779 | 0.81443 | 0.00236 | 0.00046946 | 0.01842 |
| **6** | 0.06960 | 8.87690 | 0.00123 | 0.01344 | 0.77397 | 5.425009E-8 | 0.00732 | 0.78980 | 0.00626 |
| **7** | 0.04356 | 11.22150 | 0.96543 | 0.44806 | 0.07715 | 0.09255 | 0.00394 | 0.01405 | 0.00039824 |

# Appendix O: CovidsafeBE, Regressions

## Appendix O.1: Model 1

DV= Adoption, IV= Perceived benefits, IV= perceived risks, CV= Age and gender

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 4 | 179.60925 | 44.90231 | 34.02 | <.0001 |
| **Error** | 117 | 154.40920 | 1.31974 | | |
| **Corrected total** | 121 | 334.01844 | | | |
| **Root MSE** | 1.14880 | **R-square** | 0.5377 | | |
| **Dependent mean** | 2.36475 | **R-square adj.** | 0.5219 | | |
| **Coeff Var** | 48.58002 | | | | |

| **Estimated parameters** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 1.46569 | 0.47362 | 3.09 | 0.0025 | 0 |
| BE_PB | Perceived benefits of CovidsafeBE | 1 | 0.90272 | 0.08755 | 10.31 | <.0001 | 0.68107 |
| BE_PR | Perceived risks regarding data privacy on CovidsafeBE | 1 | -0.24476 | 0.08157 | -3.00 | 0.0033 | -0.19478 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00427 | 0.00620 | -0.69 | 0.4927 | -0.04520 |
| Z2 | Gender | 1 | -0.02416 | 0.21496 | -0.11 | 0.9107 | -0.00711 |

### Individual regressions

Perceived benefits -> Adoption

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 167.72775 | 55.90925 | 39.67 | <.0001 |
| **Error** | 118 | 166.29070 | 1.40924 | | |
| **Corrected total** | 121 | 334.01844 | | | |
| **Root MSE** | 1.18712 | **R-square** | 0.5022 | | |
| **Dependent mean** | 2.36475 | **R-square adj.** | 0.4895 | | |
| **Coeff Var** | 50.20038 | | | | |

| **Estimated parameters** |
|---|

| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Standardized estimate |
|---|---|---|---|---|---|---|---|
| Intercept | Intercept | 1 | 0.36473 | 0.30945 | 1.18 | 0.2409 | 0 |
| BE_PB | Perceived benefits of CovidsafeBE | 1 | 0.94618 | 0.08923 | 10.60 | <.0001 | 0.71386 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.00156 | 0.00634 | -0.25 | 0.8058 | -0.01655 |
| Z2 | Gender | 1 | -0.05454 | 0.22188 | -0.25 | 0.8063 | -0.01604 |

Perceived risks -> Adoption

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| Source | DF | Sum of squares | Medium square | F value | Pr > F |
| Model | 3 | 39.31222 | 13.10407 | 5.25 | 0.0020 |
| Error | 118 | 294.70622 | 2.49751 | | |
| Corrected total | 121 | 334.01844 | | | |
| Root MSE | 1.58035 | R-square | 0.1177 | | |
| Dependent mean | 2.36475 | R-square adj. | 0.0953 | | |
| Coeff Var | 66.82942 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Standardized estimate |
| Intercept | Intercept | 1 | 3.34867 | 0.60115 | 5.57 | <.0001 | 0 |
| BE_PR | Perceived risks regarding data privacy on CovidsafeBE | 1 | -0.38391 | 0.11067 | -3.47 | 0.0007 | -0.30551 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.00965 | 0.00832 | 1.16 | 0.2487 | 0.10223 |
| Z2 | Gender | 1 | 0.16433 | 0.29464 | 0.56 | 0.5781 | 0.04833 |

# Appendix O.2: Model 2

DV= Perceived benefits, IV= Experience, Trust, Knowledge, Habit, CV= Age and gender

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| Source | DF | Sum of squares | Medium square | F value | Pr > F |
| Model | 6 | 30.42703 | 5.07117 | 3.65 | 0.0024 |
| Error | 115 | 159.70054 | 1.38870 | | |
| Corrected total | 121 | 190.12756 | | | |
| Root MSE | 1.17843 | R-square | 0.1600 | | |
| Dependent mean | 2.21107 | R-square adj. | 0.1162 | | |
| Coeff Var | 53.29699 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Standardized estimate |
| Intercept | Intercept | 1 | 0.34708 | 0.44742 | 0.78 | 0.4395 | 0 |
| Exp | Experience | 1 | -0.14998 | 0.26875 | -0.56 | 0.5779 | -0.04920 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| BE_HB | Habit | 1 | 0.19917 | 0.09787 | 2.04 | 0.0441 | 0.22023 |
| BE_TR | Trust | 1 | 0.22650 | 0.08804 | 2.57 | 0.0114 | 0.22888 |
| BE_KN | Knowledge | 1 | 0.04501 | 0.07254 | 0.62 | 0.5362 | 0.05693 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.00714 | 0.00766 | 0.93 | 0.3533 | 0.10032 |
| Z2 | Gender | 1 | 0.06539 | 0.23084 | 0.28 | 0.7775 | 0.02549 |

**Individual regressions**

Experience -> Perceived benefits

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 13.30788 | 4.43596 | 2.96 | 0.0351 |
| **Error** | 118 | 176.81968 | 1.49847 | | |
| **Corrected total** | 121 | 190.12756 | | | |
| **Root MSE** | 1.22412 | **R-square** | 0.0700 | | |
| **Dependent mean** | 2.21107 | **R-square adj.** | 0.0464 | | |
| **Coeff Var** | 55.36339 | | | | |

| **Estimated parameters** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 1.46501 | 0.30525 | 4.80 | <.0001 | 0 |
| Exp | Experience | 1 | -0.09737 | 0.27298 | -0.36 | 0.7220 | -0.03194 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.01736 | 0.00636 | 2.73 | 0.0073 | 0.24389 |
| Z2 | Gender | 1 | 0.18880 | 0.22876 | 0.83 | 0.4109 | 0.07360 |

Trust -> Perceived benefits

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 22.91473 | 7.63824 | 5.39 | 0.0016 |
| **Error** | 118 | 167.21283 | 1.41706 | | |
| **Corrected total** | 121 | 190.12756 | | | |
| **Root MSE** | 1.19040 | **R-square** | 0.1205 | | |
| **Dependent mean** | 2.21107 | **R-square adj.** | 0.0982 | | |
| **Coeff Var** | 53.83840 | | | | |

| **Estimated parameters** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 0.68120 | 0.40169 | 1.70 | 0.0925 | 0 |
| BE_TR | Trust | 1 | 0.22779 | 0.08663 | 2.63 | 0.0097 | 0.23018 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.01762 | 0.00616 | 2.86 | 0.0050 | 0.24751 |
| Z2 | Gender | 1 | 0.09719 | 0.22491 | 0.43 | 0.6664 | 0.03789 |

Knowledge -> Perceived benefits

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 15.12074 | 5.04025 | 3.40 | 0.0202 |
| **Error** | 118 | 175.00682 | 1.48311 | | |
| **Corrected total** | 121 | 190.12756 | | | |
| **Root MSE** | 1.21783 | **R-square** | 0.0795 | | |
| **Dependent mean** | 2.21107 | **R-square adj.** | 0.0561 | | |
| **Coeff Var** | 55.07885 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 1.18205 | 0.36021 | 3.28 | 0.0014 | 0 |
| BE_KN | Knowledge | 1 | 0.08546 | 0.07353 | 1.16 | 0.2475 | 0.10811 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.01631 | 0.00640 | 2.55 | 0.0121 | 0.22905 |
| Z2 | Gender | 1 | 0.12407 | 0.23499 | 0.53 | 0.5985 | 0.04837 |

Habit -> Perceived benefits

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 19.68625 | 6.56208 | 4.54 | 0.0047 |
| **Error** | 118 | 170.44132 | 1.44442 | | |
| **Corrected total** | 121 | 190.12756 | | | |
| **Root MSE** | 1.20184 | **R-square** | 0.1035 | | |
| **Dependent mean** | 2.21107 | **R-square adj.** | 0.0808 | | |
| **Coeff Var** | 54.35566 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 1.15905 | 0.31269 | 3.71 | 0.0003 | 0 |
| BE_HB | Habit | 1 | 0.21038 | 0.09865 | 2.13 | 0.0350 | 0.23262 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.00762 | 0.00778 | 0.98 | 0.3290 | 0.10708 |
| Z2 | Gender | 1 | 0.21041 | 0.22406 | 0.94 | 0.3496 | 0.08202 |

# Appendix O.3: Model 3

DV= Perceived risks, IV= Experience, Trust, Knowledge, Habit, CV= Age and gender

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 6 | 59.24117 | 9.87353 | 7.46 | <.0001 |
| **Error** | 115 | 152.28979 | 1.32426 | | |
| **Corrected total** | 121 | 211.53097 | | | |

| | | | |
|---|---|---|---|
| **Root MSE** | 1.15076 | **R-square** | 0.2801 |
| **Dependent mean** | 3.76776 | **R-square adj.** | 0.2425 |
| **Coeff Var** | 30.54241 | | |

**Estimated parameters**

| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Standardized estimate |
|---|---|---|---|---|---|---|---|
| Intercept | Intercept | 1 | 6.14522 | 0.43691 | 14.07 | <.0001 | 0 |
| Exp | Experience | 1 | -0.38133 | 0.26244 | -1.45 | 0.1489 | -0.11859 |
| BE_HB | Habit | 1 | 0.02761 | 0.09557 | 0.29 | 0.7732 | 0.02894 |
| BE_TR | Trust | 1 | -0.43896 | 0.08597 | -5.11 | <.0001 | -0.42052 |
| BE_KN | Knowledge | 1 | -0.12339 | 0.07084 | -1.74 | 0.0842 | -0.14797 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.01458 | 0.00748 | -1.95 | 0.0538 | -0.19414 |
| Z2 | Gender | 1 | 0.35811 | 0.22542 | 1.59 | 0.1149 | 0.13235 |

## Individual regressions

Experience -> Perceived risks

**Variance analysis**

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| **Model** | 3 | 15.73174 | 5.24391 | 3.16 | 0.0273 |
| **Error** | 118 | 195.79923 | 1.65932 | | |
| **Corrected total** | 121 | 211.53097 | | | |

| | | | |
|---|---|---|---|
| **Root MSE** | 1.28814 | **R-square** | 0.0744 |
| **Dependent mean** | 3.76776 | **R-square adj.** | 0.0508 |
| **Coeff Var** | 34.18860 | | |

**Estimated parameters**

| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Standardized estimate |
|---|---|---|---|---|---|---|---|
| Intercept | Intercept | 1 | 4.46107 | 0.32122 | 13.89 | <.0001 | 0 |
| Exp | Experience | 1 | -0.63523 | 0.28725 | -2.21 | 0.0289 | -0.19756 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.01569 | 0.00670 | -2.34 | 0.0208 | -0.20895 |
| Z2 | Gender | 1 | 0.04896 | 0.24073 | 0.20 | 0.8392 | 0.01810 |

Trust -> Perceived risks

**Variance analysis**

| Source | DF | Sum of squares | Medium square | F value | Pr > F |
|---|---|---|---|---|---|
| **Model** | 3 | 51.88922 | 17.29641 | 12.78 | <.0001 |
| **Error** | 118 | 159.64175 | 1.35290 | | |
| **Corrected total** | 121 | 211.53097 | | | |

| | | | |
|---|---|---|---|
| **Root MSE** | 1.16314 | **R-square** | 0.2453 |
| **Dependent mean** | 3.76776 | **R-square adj.** | 0.2261 |
| **Coeff Var** | 30.87088 | | |

**Estimated parameters**

| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Standardized estimate |
|---|---|---|---|---|---|---|---|
| Intercept | Intercept | 1 | 5.83932 | 0.39249 | 14.88 | <.0001 | 0 |
| BE_TR | Trust | 1 | -0.48423 | 0.08465 | -5.72 | <.0001 | -0.46389 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.01423 | 0.00602 | -2.37 | 0.0197 | -0.18944 |
| Z2 | Gender | 1 | 0.29743 | 0.21976 | 1.35 | 0.1785 | 0.10992 |

Knowledge -> Perceived risks

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| Source | DF | Sum of squares | Medium square | F value | Pr > F |
| Model | 3 | 17.67820 | 5.89273 | 3.59 | 0.0159 |
| Error | 118 | 193.85277 | 1.64282 | | |
| Corrected total | 121 | 211.53097 | | | |
| Root MSE | 1.28173 | R-square | 0.0836 | | |
| Dependent mean | 3.76776 | R-square adj. | 0.0603 | | |
| Coeff Var | 34.01824 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Standardized estimate |
| Intercept | Intercept | 1 | 4.80343 | 0.37911 | 12.67 | <.0001 | 0 |
| BE_KN | Knowledge | 1 | -0.19152 | 0.07739 | -2.47 | 0.0148 | -0.22968 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | -0.01128 | 0.00673 | -1.68 | 0.0963 | -0.15025 |
| Z2 | Gender | 1 | 0.24845 | 0.24732 | 1.00 | 0.3172 | 0.09182 |

Habit -> Perceived risks

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| Source | DF | Sum of squares | Medium square | F value | Pr > F |
| Model | 3 | 7.78488 | 2.59496 | 1.50 | 0.2174 |
| Error | 118 | 203.74609 | 1.72666 | | |
| Corrected total | 121 | 211.53097 | | | |

# Appendix P: CovidsafeBE, Moderation analysis

## Appendix P.1: Transparency

| Model Summary | | | | | | |
|---|---|---|---|---|---|---|
| R | R-sq | MSE | F | df1 | df2 | p |
| 0.3454 | 0.1193 | 2.4930 | 5.3272 | 3.0000 | 118.0000 | 0.0018 |
| **Model** | | | | | | |
| | coeff | se | t | p | LLCI | ULCI |
| constant | 5.5508 | 1.2690 | 4.3743 | 0.0000 | 3.0379 | 8.0637 |
| BE_PR | -0.8093 | 0.3213 | -2.5183 | 0.0131 | -1.4456 | -0.1729 |
| BE_TRP | -0.4207 | 0.3038 | -1.3850 | 0.1687 | -1.0222 | 0.1808 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Int_1** | 0.1023 | 0.0773 | 1.3233 | 0.1883 | -0.0508 | 0.2555 |

Since there the moderator is not significant, it is interesting to analyze if transparency has a direct impact on the adoption of the app.

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 9.82179 | 3.27393 | 1.19 | 0.3160 |
| **Error** | 118 | 324.19665 | 2.74743 | | |
| **Corrected total** | 121 | 334.01844 | | | |

# Appendix P.2: Control

| **Model Summary** | | | | | | |
|---|---|---|---|---|---|---|
| **R** | **R-sq** | **MSE** | **F** | **df1** | **df2** | **p** |
| 0.3682 | 0.1356 | 2.4469 | 6.1687 | 3.0000 | 118.0000 | 0.0006 |
| **Model** | | | | | | |
| | **coeff** | **se** | **t** | **p** | **LLCI** | **ULCI** |
| **constant** | 1.0447 | 1.5069 | 0.6933 | 0.4895 | -1.9394 | 4.0288 |
| **BE_PR** | 0.2820 | 0.3559 | 0.7924 | 0.4297 | -0.4228 | 0.9867 |
| **BE_C** | 0.5653 | 0.2770 | 2.0407 | 0.0435 | 0.0167 | 1.1138 |
| **Int_1** | -0.1437 | 0.0761 | -1.8875 | 0.0616 | -0.2944 | 0.0071 |

| **Variance analysis** | | | | | |
|---|---|---|---|---|---|
| **Source** | **DF** | **Sum of squares** | **Medium square** | **F value** | **Pr > F** |
| **Model** | 3 | 24.78568 | 8.26189 | 3.15 | 0.0275 |
| **Error** | 118 | 309.23276 | 2.62062 | | |
| **Corrected total** | 121 | 334.01844 | | | |
| **Root MSE** | 1.61883 | **R-square** | 0.0742 | | |
| **Dependent mean** | 2.36475 | **R-square adj.** | 0.0507 | | |
| **Coeff Var** | 68.45667 | | | | |

| **Estimated parameters** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Label** | **DF** | **Parameter estimate** | **Standard error** | **t value** | **Pr > \|t\|** | **Standardized estimate** |
| Intercept | Intercept | 1 | 0.73549 | 0.55777 | 1.32 | 0.1898 | 0 |
| BE_C | Control over CovidsafeBE | 1 | 0.28352 | 0.11648 | 2.43 | 0.0164 | 0.22534 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.00900 | 0.00874 | 1.03 | 0.3051 | 0.09537 |
| Z2 | Gender | 1 | 0.10187 | 0.30187 | 0.34 | 0.7364 | 0.02996 |

# Appendix P.3: Bandwagon

| **Model Summary** | | | | | | |
|---|---|---|---|---|---|---|
| **R** | **R-sq** | **MSE** | **F** | **df1** | **df2** | **p** |
| 0.4295 | 0.1845 | 2.3084 | 8.8990 | 3.0000 | 118.0000 | 0.0000 |

| Model | | | | | | |
|---|---|---|---|---|---|---|
| | coeff | se | t | p | LLCI | ULCI |
| constant | 2.9860 | 1.0076 | 2.9634 | 0.0037 | 0.9906 | 4.9814 |
| BE_PR | -0.4464 | 0.2592 | -1.7225 | 0.0876 | -0.9597 | 0.0668 |
| BE_BW | 0.3370 | 0.3779 | 0.8918 | 0.3743 | -0.4113 | 1.0853 |
| Int_1 | 0.0220 | 0.0991 | 0.2215 | 0.8251 | -0.1744 | 0.2183 |

Since there the moderator is not significant, it is interesting to analyze if bandwagon has a direct impact on the adoption of the app.

| Variance analysis | | | | | |
|---|---|---|---|---|---|
| Source | DF | Sum of squares | Medium square | F value | Pr > F |
| Model | 3 | 29.68811 | 9.89604 | 3.84 | 0.0116 |
| Error | 118 | 304.33033 | 2.57907 | | |
| Corrected total | 121 | 334.01844 | | | |
| Root MSE | 1.60595 | R-square | 0.0889 | | |
| Dependent mean | 2.36475 | R-square adj. | 0.0657 | | |
| Coeff Var | 67.91186 | | | | |

| Estimated parameters | | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | Label | DF | Parameter estimate | Standard error | t value | Pr > \|t\| | Standardized estimate |
| Intercept | Intercept | 1 | 1.12724 | 0.43549 | 2.59 | 0.0109 | 0 |
| BE_BW | Bandwagon | 1 | 0.41605 | 0.14782 | 2.81 | 0.0057 | 0.28205 |
| Age | How old are you? (from 15.5 to 80 year's old) | 1 | 0.00227 | 0.00947 | 0.24 | 0.8107 | 0.02409 |
| Z2 | Gender | 1 | 0.16214 | 0.29946 | 0.54 | 0.5892 | 0.04769 |